2010

Predicting cyanobacteria blooms in 50 lakes of Northwest Washington

Chandra T. (Chandra Terezina) Llewellyn
Western Washington University

PREDICTING CYANOBACTERIA BLOOMS IN 50 LAKES OF NORTHWEST WASHINGTON

By

Chandra T. Llewellyn

Accepted in Partial Completion

of the Requirements for the Degree

Master of Science

Moheb A. Ghali, Dean of the Graduate School

ADVISORY COMMITTEE

Co-Chair, Dr. Robin A. Matthews

Co-Chair, Dr. David U. Hooper

Dr. Merrill A. Peterson

MASTER'S THESIS

In presenting this thesis in partial fulfillment of the requirements for a master's degree at Western Washington University, I grant to Western Washington University the non-exclusive royalty-free right to archive, reproduce, distribute, and display the thesis in any and all forms, including electronic format, via any digital library mechanisms maintained by WWU.

I represent and warrant this is my original work, and does not infringe or violate any rights of others. I warrant that I have obtained written permissions from the owner of any third party copyrighted material included in these files.

I acknowledge that I retain ownership rights to the copyright of this work, including but not limited to the right to use all or part of this work in future works, such as articles or books.

Library users are granted permission for individual, research and non-commercial reproduction of this work for educational purposes only. Any further digital posting of this document requires specific permission from the author.

Any copying or publication of this thesis for commercial purposes, or for financial gain, is not allowed without my written permission.

Chandra Llewellyn

September 28, 2010

PREDICTING CYANOBACTERIA BLOOMS IN 50 LAKES OF NORTHWEST WASHINGTON

A Thesis

Presented to

The Faculty of

Western Washington University

In Partial Fulfillment

Of the Requirements for the Degree

Master of Science

By

Chandra T. Llewellyn

September 2010

Abstract

Eutrophication is one of the foremost problems affecting our freshwater resources. Excessive nutrient loading impacts freshwater lakes by altering ecosystem processes and degrading water quality, often resulting in human-induced eutrophication. Worldwide, cyanobacteria blooms occur in many anthropogenically eutrophic lakes. Such blooms are of increasing concern in the Pacific Northwest because they negatively affect lake system and function. A major concern is their unpredictable production of toxins, which can be deadly to animals, including humans. Therefore, an improved understanding of the incidence and persistence of cyanobacteria blooms is a critical aspect of protecting our water supply.

The goal of this thesis was to attempt to create a predictive model based on simple water quality characteristics that would classify lakes according to bloom status using a multivariate statistical approach. Additional possible bloom contributors such as, light availability, landscape properties, N:P ratios or other interactive effects were not investigated in this study. During 2007-2009, 50 lakes in Northwest Washington were sampled to measure standard water quality (water chemistry) parameters as part of the Institute of Watershed Studies' (IWS) small lakes monitoring project. In addition, algal samples were collected during 2007-2009. The IWS study created a water quality baseline for many previously unmonitored lakes and revealed that a number of lakes experienced cyanobacteria blooms. Previous studies have used high phosphorus as an indicator of cyanobacteria blooms. I tested phosphorus, as well as chlorophyll, as possible indicators of cyanobacteria blooms.

Based on hierarchical, Kmeans and non-metric clustering, the lakes sampled by IWS can be clustered into two groups based on differences in conductivity, alkalinity, total phosphorus and turbidity. However, chlorophyll and phosphorus concentrations did not predict lakes that were dominated by cyanobacteria blooms. High phosphorus levels were usually associated with high chlorophyll levels, but high chlorophyll levels were not always associated with cyanobacteria dominance. Using the water chemistry, data high phosphorus was a good indicator of algal blooms, but could not be used as an *exclusive* predictor of cyanobacteria blooms. Linear discriminants analysis was used to build a predictive model based on the 2007-2008 water quality data to try to classify the 2009 samples by cyanobacteria dominance. The model was unsuccessful (30% success rate) in predicting cyanobacteria blooms within the 2009 data. Despite the fact that algal blooms are fairly predictable using water chemistry data, this study highlights the complexity of predicting harmful cyanobacteria blooms in the Pacific Northwest.

Acknowledgements

I am sincerely grateful to my advisor Dr. Robin A Matthews. I very much appreciate her guidance, support, expertise, compassion and dedication to science. Thank you to my committee member and co-advisor, Dr. David Hooper; in particular, for his comments and scientific insight. Thank you to my committee member Dr. Merrill Peterson, for his valuable guidance in the graduate school process, knowledge and insight.

I am grateful to the Institute for Watershed Studies, without which this research would not be possible. Their data collection during 2007-2009 was meticulous and thorough. I am thankful to the staff of the Washington Department of Ecology for the conversations and shared resources. Thank you to GIS specialist, Stefan Freelan for his humor and expertise. Many thanks to the WWU faculty and my fellow WWU graduate students: Ben Miner, Melissa Miner, Emily Grason, Tasha Johnson, Susan Dickerson and Austen Thomas. I want to thank Laura Pavliscak for her unconditional support and encouragement; especially when I wanted to give up.

In addition, thank you to my dear friends alongside whom I have worked over the past decade in the name of science, be it in the high alpine, the Mojave desert, the Bering Sea or around the globe. Most of all, I would like to thank Corey Rubinfeld and Neva, for their unconditional love, support and unfaltering belief in accomplishing my goals. I could not ask for a better family.

Last, thank you to Western Washington University and the WWU Biology Department for my funding. I will do my best to use this education wisely.

Table of Contents

Abstract iv
Acknowledgements vi
List of Figures ix
List of Tables xii
Introduction 1
Cyanobacteria 2
Toxic Cyanobacteria 4
Washington State Response to Cyanobacteria Harmful Algal Blooms 5
Predicting Cyanobacteria Blooms 7
Thesis Questions 10
Methods 11
Sample Collection 11
Chemical Analysis 12
Algal Counts 12
Categorical Data 13
Data Methods 15
Statistical Analysis 17
Clustering Analysis 18
Ordination 19
Results and Discussion 20
Hypothesis #1: Based on water chemistry, lakes can be clustered or partitioned into unique groups. 20
Hypothesis #2: Phosphorus will be an important water chemistry parameter that is associated with phytoplankton blooms and chemical features in the lakes. 23
Hypothesis #3: The lakes will have unique chemical features that can be used to predict whether lakes are likely to develop cyanobacteria blooms. 26
Other Factors to Consider 31
Conclusion 32
Literature Cited 68
Appendix 1 74

Water Chemistry Parameters Measured for the Small Lakes Monitoring Project 74
Appendix 2. 79
Detailed Lake Descriptions and GIS Maps 79
Appendix 3. 152
Statistical Appendix 152

List of Figures

Figure 1. Summary of ecological responses and impacts associated with blooms of cyanobacteria (redrawn with permission, K. Havens, 2008). 34

Figure 2. Map showing the location of lakes that were sampled by the Institute for Watershed Studies for the small lakes monitoring project, 2007-2009. 35

Figure 3. Correlation between alkalinity and conductivity in the lakes sampled by the Institute for Watershed Studies for the small lakes monitoring project, 2007-2009. 36

Figure 4. Correlation between chlorophyll and total phosphorus in the lakes sampled by the Institute for Watershed Studies for the small lakes monitoring project, 2007-2009. 37

Figure 6. Hierarchical agglomerative clustering for all lake samples with high elevation lakes removed (squared Euclidean distance and Ward's cluster method) 39

Figure 7. Summary of Kmeans clusters and total phosphorus groups plotted by turbidity and nitrate. All low phosphorus lake samples were all placed in Kmeans Cluster 1, along with 30 of the high phosphorus lake samples. 40

Figure 8. Summary of Kmeans clusters and chlorophyll groups plotted by turbidity and nitrate. All but two low chlorophyll lakes were in Cluster 1; high chlorophyll lakes were split between both Kmeans clusters. 41

Figure 9. Summary of non-metric clusters and chlorophyll groups plotted by alkalinity and conductivity. Non-metric cluster runs yielded consistent results (10/10 runs)..... 42

Figure 10. Summary of non-metric clusters and total phosphorus groups plotted by alkalinity and conductivity. Non-metric cluster runs yielded consistent results (10/10 runs)43

Figure 11. Principal components ordination of the lake samples showing chlorophyll categorical groups (chlorophyll omitted as a response variable). 44

Figure 12. Principal components ordination of the lake samples showing phosphorus categorical groups (total phosphorus omitted as a response variable). 45

Figure 13. Summary of Kmeans clusters and cyanobacteria dominance groups plotted by turbidity and nitrate. 46

Figure 14. Summary of non-metric clusters and cyanobacteria dominance groups plotted by alkalinity and conductivity. Non-metric cluster runs yield consistent results (9/10 runs)..... 47

Figure 15. Principal components variable loading scores for the water chemistry data..... 48

Figure 16. Principal components ordination of the lake samples based on water chemistry showing algal dominance groups. 49

Figure 17. Linear discriminant ordination of the 2009 IWS small lakes samples based on a model built from the 2007-2008 data..... 50

Figure 18. The lake samples graphed with algal groups. The lakes are plotted by chlorophyll and phosphorus. High chlorophyll and high phosphorus are usually indicative of algal blooms, including cyanobacteria blooms. Dashed lines represent 10 µg/L chlorophyll and 20 µgP/L phosphorus 51
Figure 19. GIS map of Armstrong Lake, Snohomish County, WA. 101
Figure 20. GIS map of Lower Bagley Lake, Whatcom County, WA. 102
Figure 21. GIS map of Upper Bagley Lake, Whatcom County, WA. 103
Figure 22. GIS map of Beaver Lake, Skagit County, WA. 104
Figure 23. GIS map of Big Lake Skagit County, WA. 105
Figure 24. GIS map of Bug Lake, Whatcom County, WA. 106
Figure 25. GIS map of Cain Lake, Whatcom County, WA. 107
Figure 26. GIS map of Lake Campbell, Skagit County, WA. 108
Figure 27. GIS map of Canyon Lake, Whatcom County, WA 109
Figure 28. GIS map of Lake Cavanaugh, Skagit County, WA 110
Figure 29. GIS map of Cedar Lake, Whatcom County, WA 111
Figure 30. GIS map of Clear Lake, Skagit County, WA 112
Figure 31. GIS map of Crabapple Lake, Snohomish County, WA 113
Figure 32. GIS map of Cranberry Lake, Island County, WA 114
Figure 33. GIS map of Deer Lake, Island County, WA 115
Figure 34. GIS map of Erie Lake, Skagit County, WA 116
Figure 35. GIS map of Fazon Lake, Whatcom County, WA 117
Figure 36. GIS map of Lake Goodwin, Snohomish County, WA 118
Figure 37. GIS map of Lake Goss, Island County, WA 119
Figure 38. GIS map of Lake Grandy, Skagit County, WA 120
Figure 39. GIS map of Heart Lake, Skagit County, WA 121
Figure 40. GIS map of Honeymoon Lake, Island County, WA 122
Figure 41. GIS map of Howard Lake, Snohomish County, WA 123
Figure 42. GIS map of Ketchum Lake, Snohomish County, WA 124
Figure 43. GIS map of Ki Lake, Snohomish County, WA 125
Figure 44. GIS map of Loma Lake, Snohomish County, WA 126
Figure 45. GIS map of Lone Lake, Island County, WA 127
Figure 46. GIS map of Lake Louise, Whatcom County, WA 128

Figure 47. GIS map of Martha Lake, Snohomish County, WA 129
Figure 48. GIS map of McMurray Lake, Skagit County, WA 130
Figure 49. GIS map of Mirror Lake, Whatcom County, WA 131
Figure 50. GIS map of Lake Padden, Whatcom County, WA 132
Figure 51. GIS map of Pass Lake, Skagit County, WA 133
Figure 52. GIS map of Picture Lake, Whatcom County, WA 134
Figure 53. GIS map of Pine Lake, Whatcom County, WA 135
Figure 54. GIS map of Reed Lake, Whatcom County, WA 136
Figure 55. GIS map of Shoecraft Lake, Snohomish County, WA 137
Figure 56. GIS map of Silver Lake, Whatcom County, WA 138
Figure 57. GIS map of Sixteen Lake, Skagit County, WA 139
Figure 58. GIS map of Squalicum Lake, Whatcom County, WA 140
Figure 59. GIS map of Squires Lake, Whatcom/Skagit County, WA 141
Figure 60. GIS map of Summer Lake, Skagit County, WA 142
Figure 61. GIS map of Sunday Lake, Snohomish County, WA 143
Figure 62. GIS map of Sunset Lake, Whatcom County, WA 144
Figure 63. GIS map of Tennant Lake, Whatcom County, WA 145
Figure 64. GIS map of Lake Terrell, Whatcom County, WA 146
Figure 65. GIS map of Toad Lake, Whatcom County, WA 147
Figure 66. GIS map of Lower Twin Lake, Whatcom County, WA 148
Figure 67. GIS map of Upper Twin Lake, Whatcom County, WA 149
Figure 68. GIS map of Vogler Lake, Skagit County, WA 150
Figure 69. GIS map of Wiser Lake, Whatcom County, WA 151

List of Tables

Table 1. Summary of toxins known to occur in cyanobacteria…..……..52

Table 2. The 50 lakes sampled as part of IWS small lakes monitoring project……..…..53

Table 3. Summary of water chemistry analytical methods and detection limits used by the IWS for the small lakes monitoring project…….……....54

Table 4. Unique algal taxa identified and counted for the IWS's small lakes monitoring project……...…55

Table 5. Summary of algal dominance in the lakes sampled by IWS (2007-2009).…….....58

Table 6. Summary of Kruskal-Wallis comparisons between algal categorical groups……..59

Table 7. Summary of Kruskal-Wallis comparisons between chlorophyll categorical groups……...…60

Table 8. Summary of Kruskal-Wallis comparisons between phosphorus categorical groups……...…61

Table 9. Summary of Kruskal-Wallis comparisons between high and low elevation groups……...…62

Table 10. Comparison between high and low elevation lake samples in the small lakes project.....63

Table 11. Summary of the hierarchical agglomerative clustering groups by lake ……...……..64

Table 12. Summary of the hierarchical agglomerative clustering split lake…..…….…….65

Table 13. Kmeans clusters and categorical groups summary statistics…….…….…….66

Table 14. Results for 3 Riffle analyses testing with: dominance groups, chlorophyll groups and phosphorus groups…….....67

Table 15. Kendall's tau correlation coefficients between environmental water chemistry variables.....153

Table 16. Summary statistics for all lakes sampled in the small lakes monitoring project (high elevations lakes are removed).……....154

Table 17. The data for my study (organized by year) collected by the Institute for Watershed Studies for their small lakes monitoring project 2007-2009…….……..155

Introduction

Eutrophication is the leading water quality issue for the majority of freshwater and marine ecosystems in the world (Smith and Schindler 2009). Nitrogen and phosphorus, in the forms of agricultural fertilizers, industrial pollutants, storm drain runoff and sewage, flow into aquatic ecosystems, causing human-induced or "cultural" eutrophication (Havens et al. 2003, Gilbert et al. 2006, Smith 2006). Cultural eutrophication is defined as excessive phytoplankton or macrophyte growth as a result of nutrient enrichment by human activity (Smith and Schindler 2009).

There are many adverse effects of eutrophication. Increases in primary productivity, known as a bloom, can simplify biotic communities and lead to anoxic conditions, which negatively impact both lake system and function (Anderson 1997, Wetzel 2001, Stanley 2003). Thus, freshwater lakes are indicators of conditions in upstream waterways and surrounding watersheds, with phytoplankton blooms commonly used as water chemistry indicators to identify lakes affected by anthropogenic impacts (Wetzel 2001, Downing et al. 2001). Therefore, our current approach to mitigating eutrophication in lakes is to focus on minimizing nutrient inputs into our waterways as well as protecting our water sources from further development. This has been successful in diminishing algal blooms that respond to nitrogen and phosphorus levels (Smith and Schindler 2009). Currently, eutrophication accounts for half of the impaired lakes in the United States (EPA 1996).

In addition to algal blooms, eutrophication can lead to cyanobacteria dominance, which can contribute further to ecosystem degradation (Wetzel 2001, Havens 2008, and Figure 1). Cyanobacteria harmful algal blooms (CHABs) are an increasing problem

occurring globally in anthropogenically eutrophic lakes, creating significant concern for recreation, ecosystem integrity (nutrient cycles, oxygen availability and water toxicity) and human health (Dokulil and Teubner 2000, Downing et al. 2001, Gilbert et al. 2006, Smith 2006, Havens 2008). Predicting and mitigating cyanobacteria blooms has not been as successful as predicting algal blooms.

There are several negative effects associated with cyanobacteria blooms including reduced transparency in the water column, decreased biodiversity, explosion of primary production and oxygen depletion (Smith 2006, Havens 2008, Paul 2008). All of these effects can alter food web interactions. Cyanobacteria blooms produce bad smelling, mucilaginous clumps of senescing cells on the lake surface (Downing et al. 2001). The blooms affect water taste and odor, necessitating costly water filtration (Dodds et al. 2009). Cyanobacteria blooms can also produce toxins killing aquatic and terrestrial wildlife and domestic animals (Sivonen 1996, Dokulil and Teubner 2000, Wetzel 2001). Additionally, cyanobacteria toxins can cause illness and death in humans (Sivonen 1996). Therefore, an improved understanding of the incidence and persistence of cyanobacteria blooms is a critical aspect of protecting ecosystem processes such as nutrient cycles and oxygen availability, as well as human health via the water supply.

Cyanobacteria

Cyanobacteria can persist in many environments, and are found in aquatic and terrestrial systems from the Arctic to Antarctica (Smith and Schindler 2009). They have a cosmopolitan distribution and can even be found in desert soils and in the fur of polar bears (*Ursus maritimus*). Cyanobacteria are part of the Domain Bacteria, Phylum Cyanobacteria. Taxonomically, they are a vast group that has been reclassified repeatedly as scientists learn

more about their genetic structure. Cyanobacteria have been around roughly 3 billion years (Paul 2008), and are thought to be one of the earliest organisms on earth. According to the fossil record, cyanobacteria thrived following mass extinction events and were the dominant organisms on earth 250 million years ago (Paul 2008). Many species of cyanobacteria are able to switch between photoautotrophy and heterotrophy, in response to the availability of light, nutrients, and suitable organic carbon sources. This ability makes cyanobacteria excellent resource competitors that are highly successful in dominating lake systems under varying conditions. Based on their distribution and evolutionary history, cyanobacteria will most likely continue to thrive with increased temperatures from global climate change (Paul 2008, Davis et al. 2009). This could result in further increased frequency and abundance of cyanobacteria blooms.

Many cyanobacteria (e.g., *Aphanizomenon flos-aquae, Cylindrospermopsis, Anabaena*) are able to fix dissolved nitrogen gas (N_2), using specialized cells called heterocysts. These taxa can access nitrogen when dissolved inorganic nitrogen concentrations are too low for other types of algae to extract nitrogen from the water column (Shapiro 1990, Dokulil and Teubner 2000). As the cyanobacteria cells die, the fixed nitrogen becomes available, which may increase overall availability in nitrogen-limited lakes. However, cyanobacteria blooms can negatively affect the ecosystem by dominating the water column, out-competing other algae for nutrients and light and creating dense blooms in which other organisms cannot survive (Karlsson et al. 2009, Wetzel 2001).

When phosphorus is plentiful, some genera of cyanobacteria take up excess phosphorus through a process known as luxury consumption. The stored phosphorus is used to sustain growth and metabolism when ambient phosphorus concentrations are low

(Pettersson et al. 1993, Reynolds 1998). Cyanobacteria have evolved varying methods of movement in the water column. Most taxa are motile on solid surfaces using gliding action, and many taxa (e.g., *Microcystis, Planktothrix*) can regulate buoyancy, adjusting their position in the water column with internal gas vesicles. These internal gas vesicles help limit UV exposure and provide optimal lighting for photosynthesis (Reynolds et al. 1987).

Cyanobacteria produce akinetes or "resting cells" that can stay in the water column or lake bottom until conditions are ideal for a bloom (Wetzel 2001). Akinete production is highest following summer blooms (Carey et al. 2008). In *Gloeotrichia echinulata*, the surface bloom population is linked to akinete recruitment and can account for 3-50% of the bloom (Carey et al. 2008).

Toxic Cyanobacteria

A widely researched yet poorly understood characteristic of cyanobacteria is that some strains form toxic blooms. Cyanobacteria can produce a variety of toxins, including microcystin, a hepatotoxin, and anatoxin-a, a neurotoxin (Table 1). Toxic cyanobacteria blooms can harm pets, livestock, and humans (Sivonen 1996). The purpose of toxin production by cyanobacteria is not known, but it has been suggested that these chemicals may provide a chemical defense against grazers, or may produce an allelopathic effect allowing blooms to persist in the face of competitors (Paul 2008). The toxicity of a cyanobacteria bloom can only be determined through molecular analysis, making identification both costly and time consuming. With the increased abundance and frequency of toxic blooms, it is important to understand factors that contribute to the development of cyanobacteria blooms (Havens 2008, Paul 2008).

Recent work by Davis et al. (2009) found that increased toxicity in *Microcystis* (a toxin-producing, ubiquitous cyanobacterium) was directly related to increased phosphorus availability and increased temperature. Their field research consisted of monitoring four lakes in the Northeast US over two years. Toxicity was measured based on the microcystin synthesis genes (mcyA-mcyJ), which are not possessed by non-toxic strains. In 83% of their experiments, higher temperatures yielded significantly increased growth rates of toxic *Microcystis*. For the non-toxic cyanobacteria there was a 33% increase (Davis et al. 2009). This study also found that lakes that initially did not have toxic strains of *Microcystis* became dominated by toxic strains as lake temperatures increased (Davis et al. 2009). They found that a concurrent increase in temperature and phosphorus concentrations yielded the highest growth rates of toxic *Microcystis* in all experiments. Based on such findings, scientists postulate that toxic strains of cyanobacteria will occur more frequently with continued eutrophication and climate change (Paul 2008, Davis et al. 2009).

In Washington State, cyanobacteria toxins have been linked to deaths in birds, fish and dogs (personal communication, Tricia Shoblom, Washington Department of Ecology, January 2010). Throughout the Pacific Northwest, there is growing concern about toxic cyanobacteria blooms, especially because the blooms seem to be occurring with greater frequency (personal communication, Tricia Shoblom, Washington Department of Ecology, January 2010).

Washington State Response to Cyanobacteria Harmful Algal Blooms

The Washington Department of Ecology monitors algal blooms under its Freshwater Algae Control Program (FACP). This program allows the public to report and monitor algal blooms in local lakes. Once the Department of Ecology is notified of a bloom, a sample is

collected and shipped to the toxicology lab in King County, Washington. If the sample tests positive for a toxin, there are several possible scenarios. Depending on the toxicity levels, the Washington State Health Department will restrict or prohibit access to the lake. Multiple samples may be needed to identify and monitor the bloom. Monitoring continues every two weeks until either the bloom or toxicity has subsided (Washington Department of Ecology, 2008).

Washington State has created regulations to limit nutrient loading in freshwater and coastal marine ecosystems. In March of 2006, Washington State House Bill 2322 was approved, requiring all dishwashing detergents in Washington State to contain no more than 0.5% phosphorus. The bill was created to reduce algal blooms as a direct result of phosphorus loading (WA: EHB 2322.SL, 2006). Since this bill, improvements have been made throughout Washington State. State regulations and non-profit, citizen organizations have significantly increased the public awareness surrounding the issues of water quality and cyanobacteria harmful algal blooms. Two state organizations that focus on lake issues are the Washington State Lake Protection Association and North Cascades Audubon Society. The Washington State Lake Protection Association is a non-profit organization formed by concerned citizens in 1986 "to educate, inform, assist in research, awareness and to help protect local lakes for the future" (WALPA, 2010). They are affiliated with the North American Lake Management Society (NALMS), a national organization focused on creating partnerships between scientists, professionals and citizens for the protection and management of lakes and reservoirs (NALMS, 2010). Another citizen group, North Cascades Audubon Society (NCAS), focuses on habitat conservation for migratory and resident bird populations. Their mission has created involvement in lake restoration and local watershed issues, as it

pertains to bird habitat. North Cascades Audubon Society gives funding to scientific research, as well as conservation and education outreach efforts, to promote awareness and conservation (NCAS, 2010). These organizations have been crucial in spreading awareness and organizing the public in protecting Washington's freshwater resources. Still, there is a greater need for public awareness, research and government policy implementation to further protect our freshwater lakes.

Predicting Cyanobacteria Blooms

Much attention has been focused on managing cyanobacteria blooms. This effort has been more challenging and less successful than predicting algal blooms. If we could predict the onset of a cyanobacteria bloom we might be able to mitigate some of the negative effects and minimize the exposure of humans, pets and wildlife to harmful toxic blooms. Predicting cyanobacteria blooms, however, is a complex and challenging question. Patterns from one lake often do not fit the patterns in a different lake. Thus far, there have been two main approaches to modeling cyanobacteria blooms in lakes: 1) a process-based artificial neural network approach; and, 2) statistical approaches that are usually based on the chlorophyll-phosphorus relationship (Guven and Howard 2006).

Artificial neural networks have been successful in predicting cyanobacteria blooms. For example, Maier et al. (1999, 2001) successfully forecasted *Anabaena* blooms in the River Murray, Morgan, Australia. Artificial neural networks are, however, extremely complex computational models that are constructed to mimic biological neural networks (Crawley 2007). Maier et al. (2001) pointed out that their model required a costly and intensive sampling effort that generated copious amounts of data (sampling was twice weekly for 7 years).

Statistical models such as linear regressions have also been used successfully to predict cyanobacteria blooms (e.g. Dillion and Rigler 1974, Onderka 2007). These models can be built based on existing data and are often more cost effective than artificial neural networks. Early lake studies established the correlation between phosphorus and chlorophyll in lakes around the world (Sakamoto 1966, Dillon and Rigler 1974, Wetzel 2001). The positive relationship between chlorophyll (phytoplankton biomass) and total phosphorus laid the foundation of our current statistical models of phytoplankton blooms and helped shape our understanding of cyanobacteria blooms (Wetzel 2001, Havens 2008). There are exceptions to the chlorophyll-phosphorus model, however, that make predictions of algal biomass somewhat inconsistent. Recent studies redefine the chlorophyll-phosphorus relationship and incorporate additional variables into their models, including electrical conductivity, inorganic N (nitrite, nitrate), water temperature (Stanley et al. 2003) and total nitrogen/total phosphorus (TN/TP) ratio (Smith 1982). In a study using 228 lakes from the northern latitudes, Smith (1982) built a multiple regression model incorporating Sakamoto's equations on chlorophyll (Sakamoto 1966) and incorporated TN/TP ratio. The regression had improved accuracy in predicting algal biomass, including cyanobacteria blooms (Smith 1982). However, Smith noted that moderate latitude, high nutrient lakes are not suitable for these models, based on variations in total nitrogen and total phosphorus.

Another limitation of the chlorophyll-phosphorus model is that it cannot predict phytoplankton blooms in phosphorus-rich lakes. In phosphorus-rich systems, nitrogen limitation is a better predictor of chlorophyll and has successfully predicted both algal and cyanobacteria blooms (Stanley et al. 2003). For instance, a study assessing water quality in

Lake Manatee, Florida, found nitrogen limitation to be an important predictive variable in determining algal blooms (Stanley et al. 2003).

Most phytoplankton biomass models built on the chlorophyll-phosphorus relationship have success predicting algal blooms, but limited success with predicting cyanobacteria blooms (Downing et al. 2001, Guven and Howard 2006). Luxury consumption of phosphorus and the ability to fix inorganic nitrogen contribute to the inaccuracy (Reynolds 1998, Ritchie et al. 2001). It is likely that other variables are contributing to the frequency and magnitude of cyanobacteria blooms, including light, temperature, turbidity (Reynolds 1985) and cyanobacteria buoyancy (Reynolds et al. 2002, Havens 2008).

A statistical model in Slovakia used three variables: total nitrogen, total phosphorus r and temperature to predict cyanobacteria blooms. The model was successful in predicting cyanobacteria blooms in Liptovska Mara reservoir (Onderka 2007). The author also points out the main goal of the study was to build a predictive model that would assist environmental managers and health officers in deciding when sampling of plankton should occur in order to save time and costly molecular analysis (Onderka 2007).

Arguably, statistical models and artificial neural networks are narrowly constrained to the data being modeled, which limits their effectiveness when applied to other lake systems (Maier et al. 1997, Howard 2001, Guven and Howard 2006). These models have had varying success and convey the complexity of predicting cyanobacteria blooms. It appears that a combination of factors are responsible for the occurrence of cyanobacteria blooms (Dokulil and Teubner 2000, Smith 2008). Currently, there is a need for the development of novel

approaches to predicting cyanobacteria blooms that are cost effective, accessible to government agencies and timely, to mitigate the dangers of toxic blooms.

Thesis Questions

My primary objective was to determine whether water chemistry data from 50 local lakes could be used to predict the occurrence of cyanobacteria blooms within these lakes. I chose a multivariate statistical approach in the hopes of finding a cost effective, simple model that could be built from existing data and would assist water chemistry managers in predicting cyanobacteria blooms throughout northwest Washington. If I can show that lake water chemistry can accurately predict cyanobacteria blooms, agencies tasked with protecting citizens from CHABs can respond more quickly and efficiently. Based on current literature, I hypothesized that phosphorus would be the single best variable for predicting cyanobacteria blooms. Further, I predicted that lakes dominated by cyanobacteria would have unique water chemistry that could be used to distinguish bloom-forming lakes from lakes that did not develop cyanobacteria blooms.

My research hypotheses are:

1. Based on water chemistry, lakes can be clustered or partitioned into unique groups (lakes will not all have the same ranges for chemical parameters).
2. Phosphorus will be an important water chemistry parameter that will be associated with phytoplankton blooms and chemical features in the lakes.
3. The lakes will have unique chemical features that can be used to predict whether lakes are likely to develop cyanobacteria blooms.

Methods

Sample Collection

This thesis is based on water chemistry and algal data collected by the Institute for Watershed Studies (IWS) from 50 small lakes in Whatcom, Skagit, Snohomish and Island Counties as part of the Institute's small lakes monitoring project (Table 2). The lake samples were collected during the summers of 2007-2009; additional water chemistry samples were collected during spring 2007-2009, but these data were not included in the analyses for reasons described later in this section. The lakes that were selected for sampling met the following criteria: the lakes needed to be within a reasonably close proximity to Bellingham (most were <50 miles from WWU), and had to have a public access that would allow sample collection. In addition, the primary goal of the Institute's monitoring project was to provide water chemistry data for lakes that did not have on-going monitoring programs, so most lakes were relatively small (smaller lakes tend not to receive as much water chemistry funding). Because the goal was to sample as many lakes as possible, not all lakes were sampled on a regular basis; sampling depended on seasonal accessibility, funding and number of Institute employees available during sampling season. The lakes were diverse, differing in the degree of watershed development and recreational access, level of eutrophication, size, depth, development and elevation (Figure 2). For a detailed description and GIS map for each lake, see Appendix 2.

The lakes were sampled in the spring and summer using standardized water sampling techniques (Table 3). Two water samples and two phytoplankton samples were collected at each lake. One of the phytoplankton samples was preserved for algal counting using Lugol's Iodine solution (Hamilton et al. 2001). The other phytoplankton sample was placed on ice and returned to the laboratory where the live algae were identified by Dr. Robin Matthews.

When I began working on my thesis, the algal counts had been completed but Dr. Matthews, but had not been compiled (entered and verified) into an electronic data file. I constructed the algal data set and verified the data with the assistance of Dr. Matthews. Algae were identified to the lowest practical taxon, resulting in 115 unique taxa (Table 4). Some lakes were sampled multiple times during 2007-2009; other lakes were sampled only once due to seasonal accessibility and limitations on the Institute's sampling effort.

Chemical Analysis

The water chemistry data were analyzed by the Institute for Watershed Studies to measure the following variables: turbidity (NTU), conductivity (µS/cm), chlorophyll *a* (µg/L), pH, dissolved oxygen (mg/L), water temperature (Celsius), alkalinity (mg/L as $CaCO_3$), ammonium (µg-N/L), nitrate+nitrite (µg-N/L), total persulfate nitrogen (µg-N/L), soluble reactive phosphate (µg-P/L) and total persulfate phosphorus (µg-P/L). For a more detailed description of each water chemistry parameter see Table 3 and Appendix 1.

Algal Counts

Algal samples were processed for counting using methods described in Hamilton et al. (2001). A 25, 50 or 100 mL Plexiglass settling chamber was used to settle the plankton sample. The settling chamber was placed on top of a 50 x 75 mm glass microscope slide containing a 506.7 mm^2 counting cell. The settling chamber volume was determined based on the chlorophyll concentration from each lake, with smaller volumes used for lakes with high chlorophyll concentrations. The samples were allowed to settle one hour per mL based on settling chamber volume; then the algae were counted with a compound microscope.

Most counts entailed identifying and enumerating all algal taxa in 10 fields of view at 400x magnification. In a few samples, the counts were terminated after five fields because the sample contained very high densities of relatively few algal taxa (i.e., a bloom). When there were extremely high cell densities for a particular taxon (>30 per field), the cell counts were estimated using a $\log_2$ range (32-64, 64-128, 128-256, etc.) This created a data set where rare and uncommon taxa could be counted precisely, while common taxa could be ranked in terms of relative abundance. To approximate cell counts from the $\log_2$ scale, I rounded to the highest range value. For example, if the estimate was 32-64 cells, I rounded to 64 cells. This was done for consistency and to account for underestimation of cells present.

Categorical Data

Because my primary goals included looking for groups associated with water chemistry and cyanobacteria blooms, I created *a priori* categorical groups based on phosphorus levels and cyanobacteria densities. I also created categorical groups for chlorophyll to help identify patterns of association between water chemistry and algal densities.

I attempted to define cyanobacteria dominance based on the current literature but there is no consistent definition. Using the plankton data, I developed a definition of cyanobacteria dominance using the three most prolific, toxin-producing cyanobacteria: *Anabaena, Aphanizomenon* and *Microcystis*. In this definition, if these three genera of cyanobacteria cumulatively accounted for $\geq$ 50% of the algal counts, the lake was classified as dominated by cyanobacteria. These three genera are cosmopolitan and globally account for the majority of reported CHABs around the world (Paul 2008, Paerl 2008, Smith 2009). These genera frequently occur in both toxic and non-toxic forms (Anderson et al. 2002, Paerl

2008). In the 50 study lakes sampled by IWS, toxic and non-toxic forms of the three cyanobacteria blooms (*Anabaena, Aphanizomenon,* and *Microcystis*) were commonly found (Washington Department of Ecology, 2010). Using this definition for dominance, each algal sample was classified as "cyanobacteria dominated" or "other." Samples categorized as "other" might have had high or low algal densities, but the combined density of *Anabaena, Aphanizomenon* and *Microcystis* were < 50% of the count. Based on this definition, 19 lake samples (21%) were classified as being dominated by cyanobacteria and 73 lake samples (79%) were classified as being dominated by other types of algae (Table 5). It is important to note that not all genera of cyanobacteria are of concern. Cyanobacteria are ubiquitous. They occurr in most water samples, and not all genera are known bloom formers. For these reasons I focused on *Anabaena, Aphanizomenon* and *Microcystis*.

To test the *a priori* hypothesis that phosphorus was associated with cyanobacteria blooms, I defined high and low phosphorus ranges and created categorical phosphorus groups. I did the same for chlorophyll because I wanted to see whether the lake samples with high chlorophyll concentrations fell into the same categories as the cyanobacteria dominated samples.

I examined the distribution of the water chemistry data and created groups based on current literature regarding phosphorous levels. The Washington State protocol for phosphorus recommends any lake with a phosphorus level $\geq$ 20 µg-P/L requires additional monitoring and management (Washington State Legislature 173-201A-230, 2006). Based on their recommendations, I defined "low" phosphorous lake samples as having < 20 µg-P/L and "high" phosphorous lake samples as having $\geq$ 20 µg-P/L. Chlorophyll lake samples were "low" if they contained < 10 µg/L chlorophyll and "high" chlorophyll if they contained $\geq$ 10

µg/L chlorophyll. This decision was based on international guidelines designed by the World Health Organization to monitor and prevent, algae and cyanobacteria blooms (WHO 2003, EPA 2008).

Data Methods

One of the major efforts for this study was to create electronic algal data sets from the Institute for Watershed Studies' small lakes monitoring project. A significant effort went into the construction and verification of the algal data set. Constructing the data set required making a number of decisions regarding the data entry (see below). All data entry decisions were made in consultation with Dr. Matthews and the Institute for Watershed Studies staff.

Decision 1: Some of the lakes were sampled both spring and summer. Preliminary examination of the algal data, however, revealed that the spring periphyton communities were usually not well developed, especially during cold springs. Algal abundance and diversity were often very low, and many taxa were present in atypical forms such as over-wintering resting spores. Based on discussions with Dr. Matthews, we decided to omit the spring data from this study, in part because of the inconsistent algal data, and also because the spring water chemistry data are biased to include only lakes that are accessible year-round. Although the Institute is continuing to collect spring water chemistry data from some of the lakes, they have discontinued counting spring algae.

Decision 2: Two lakes, Wiser Lake and Fazon Lake, were sampled during massive cyanobacteria blooms in the summer of 2009. The samples were collected along the lakes' shorelines, which were coated with a wind-driven algal mat. The chlorophyll concentrations in these two samples were nearly an order of magnitude higher than any previously collected

chlorophyll levels, and were determined to be atypical outliers by the Institute for Watershed Studies. Both samples have been deleted from the Institute's online records, so they were excluded from my analyses.

Decision 3: Lake samples that had one or more missing value were removed. This was necessary for most of the multivariate analyses, which will automatically omit a sample if there are missing values for any of the variables. I could either remove the entire variable, or omit the individual sample. I chose to retain variables at the expense of individual samples. For consistency, all analyses were run with the same edited data set.

Decision 4: In creating the algal data set, some of the taxa were identified to different levels over the years. For example, *Ankyra juday* and *Ankyra lanceolata* were not consistently identified to species, whereas *Ankyra ancora* was always identified to species. The following algal taxa were combined to make the data sets consistent across all years:

> *Ankyra* = *A. juday* and *A. lanceolata*; *Ankyra ancora* was left separate.
>
> *Aphanizomenon* = all species of *Aphanizomenon*, including *A. flos-aquae* and *A. gracile*.
>
> *Aphanocapsa/Aphanothece* = all species of *Aphanocapsa* and *Aphanothece*.
>
> *Chroococcus* = all species of *Chroococcus*, including *C. dispersus* and *C. turgidus*.
>
> Desmids = all species of desmids were combined except *Cosmocladium* and *Closterium*.
>
> Diatoms = all species of diatoms were combined; except *Urosolenia.*
>
> *Komma/Chroomonas* = *Komma caudata* and *Chroomonas.*
>
> *Peridinium* = all species of *Peridinium*; except *P. inconspicuum*.

Statistical Analysis

The R statistical program was used for all statistical analyses (http://www.r-project.org/). To determine if the data met the assumptions for parametric tests, I used univariate and bivariate exploratory analyses. I used Quartile-Quartile plots (Q-Q plots) and box plots to examine each variable graphically, checking for non-normal distributions and homogeneity of variances (Crawley 2007). Box plots were also used to summarize the distribution of each variable. Histogram plots were used to examine the frequency distribution of each variable in the water chemistry data (Crawley 2007).

Initially, each variable was tested to determine whether the data were normally distributed (Shapiro-Wilk test) and had homoscedastic variances (Bartlett test, Fligner test) within the categories I developed for cyanobacteria dominance, chlorophyll, and total phosphorus (Crawley 2007). Next, I looked for significant univariate differences in water chemistry between my algae categorical groups ("cyanobacteria dominated" and "other" lake samples).

I used correlation analysis as an exploratory statistical tool to identify bivariate monotonic correlations between the water chemistry parameters. Preliminary examination of the data revealed that most variables were not normally distributed and had heteroscedastic variance, so I used the rank-based Kendall's tau correlation method rather than Pearson's *r* (Zar, 1999). To test differences between categorical groups (cyanobacteria dominance, total phosphorus and chlorophyll), I used the Kruskal-Wallis rank sum test, a non-parametric, rank-based alternate to the one way ANOVA (Zar, 1999, Crawley 2007).

Clustering Analysis

Clustering analysis is a method that looks for groups (clusters) in the data based on >2 measured variables. I used the minimum number of clusters that described major patterns in the data. I used three clustering methods to determine whether the lakes could be clustered into groups containing similar water chemistry features: agglomerative hierarchical clustering (Kaufman and Rousseeuw 1990), Kmeans divisive clustering (MacQueen 1967) and non-metric clustering (Matthews and Hearne 1991). Association analysis (Goodman and Kruskal 1954, Matthews et al. 1995) was used to determine whether the clusters were associated with my categorical groups for cyanobacteria dominance, chlorophyll, and phosphorus levels.

Agglomerative hierarchical clustering calculates the distance between all data points in multivariate space using all the water chemistry variables. As points are combined, distances are recalculated and the process is repeated until all points are clustered. I chose Ward's clustering method with squared Euclidean distances because it minimizes within-cluster variance (Everitt 1993).

The Kmeans clustering algorithm is a type of divisive clustering that minimizes sums of squares between cluster centers as described by MacQueen (1967). In Kmeans clustering you must request the number of groups; the output is a comparison of means between the selected numbers of groups (Crawley 2007).

Non-metric clustering is a machine learning tool that works with both parametric and nonparametric data (Matthews and Hearne 1991). Unlike hierarchical and Kmeans clustering, non-metric clustering is not based on a multivariate metric distance. Instead, each

variable is examined individually. The output includes a measurement of the proportional reduction in error score (PRE score). The PRE score is an estimate of whether the non-metric clustering groups provide a better estimate for each variable than random chance (Matthews and Hearne 1991).

Both Kmeans and non-metric clustering are stochastic, and can produce different results each time the program is run; however, if there are strong patterns in the data, the results will often be consistent. In non-metric clustering, repeated iterations will uncover the stability of clusters. A simple Chi-squared test can be used for both Kmeans and non-metric clustering to test the degree of association between known groups (e.g., my categorical groups), and the clusters identified by the program. This process is referred to as "association analysis" (Goodman and Kruskal 1954, Matthews et al. 1995).

Ordination

My primary goal was to attempt to cluster the lakes based on water chemistry and associate those clusters with algal categorical groups. In addition, I used principal components analysis (PCA) to identify important variables in the water chemistry and to look for gradients in the lake data. Principal components analysis is often used in ecology to identify dominant variables that form gradients (Crawley 2007). I used linear discriminant analysis (Venables and Ripley 2002) to attempt to predict cyanobacteria dominance in the 2007-2009 data. Linear discriminants are based on monotonic relationships among variables (i.e., correlations), and the method is often used to develop predictive multivariate models that can be used to classify new data. Linear discriminant analysis is similar to analysis of variance and regression analysis; however, it includes methods for resolving heteroscedastic variances (Venables and Ripley 2002, Crawley 2007)

Results and Discussion

The underlying purpose of my research was to determine whether I could create a predictive model for cyanobacteria dominance that was based on simple water chemistry measurements. To accomplish this, I first attempted to cluster the lakes using the 2007-2009 water chemistry data (Hypothesis 1), then looked for water chemistry patterns associated with cyanobacteria dominance (Hypothesis 3), or high/low phosphorus and chlorophyll categorical groups (Hypotheses 2). Based on preliminary analyses, I determined that the data were not normally distributed and had heteroscedastic variances, so I used non-parametric and rank-based analyses when possible. For multivariate clustering, PCA, and LDA, I selected options that help reduce the influence of outliers and heteroscedastic variance. For example, I based the PCA and LDA analyses on a correlation matrix rather than a co-variance matrix. In addition, I used multiple methods to look for consistency in the results rather than relying on a single multivariate technique.

Hypothesis #1: Based on water chemistry, lakes can be clustered or partitioned into unique groups.

I used Kendall's tau correlation analysis to test for pair-wise relationships among water chemistry variables (Appendix 3: Table 15). I omitted dissolved oxygen percent saturation because it was highly correlated and redundant with field dissolved oxygen. Correlation analysis produced 60 significant correlation pairs ($p \leq 0.05$), which was too many for meaningful analysis. Therefore, I chose a conservative (higher) tau to focus on the strongest correlations ($tau \geq 0.35$, $p \leq 0.001$). This resulted in 19 highly significant correlations (Appendix 3: Table 15). Conductivity and pH were highly correlated ($tau=0.5$, $p \leq 0.001$), as were pH and alkalinity ($tau=0.53$, $p \leq 0.001$). These three water chemistry parameters all

measure dissolved materials in the water column and were expected to be correlated. The strongest correlation in the matrix was between alkalinity and conductivity (Figure 3; tau=0.81, $p \leq 0.001$). All the lakes had relatively low alkalinity compared to lakes found in other parts of the country (Wetzel 2001, Appendix 3, Table 15). Not surprisingly, chlorophyll was correlated with total phosphorus (Figure 4; tau=0.50, $p \leq 0.001$) and total nitrogen (Appendix 3: Table 15; tau=0.47, $p \leq 0.001$). Temperature and pH had a strong correlation (tau=0.36, $p \leq 0.001$), but this may have been the result of sampling groups of lakes from the same geographic region on the same day, so the water temperature would be similar within the lake group.

I next used Kruskal-Wallis rank sum tests with Holm's correction for repeated measures to test for significant differences in chemical variables across the *a priori* categorical groups of cyanobacteria dominance (Table 6), high and low chlorophyll (Table 7) and high and low phosphorus (Table 8). The samples dominated by cyanobacteria had significantly higher chlorophyll and phosphorus levels compared to samples with other types of algae (Table 6). In fact, only soluble reactive phosphorus and ammonia concentrations were not significantly different between samples dominated by cyanobacteria and those dominated by other types of algae. Similarly, most of the water chemistry medians were significantly different between the high and low chlorophyll groups and the high and low phosphorus groups (Tables 7-8).

In addition to my original algal categories, I tested whether there were significant differences in water chemistry based on lake elevation. I included this new category because it quickly became apparent that there was a small subset of atypical, high elevation lakes that had distinctly different water chemistry compared to nearly all other lakes in the data set.

The high elevation lakes had significantly different medians for all water chemistry parameters, and were characterized by exceptionally low chlorophyll and phosphorus concentrations (Table 9). I clustered the lakes using agglomerative hierarchical clustering, partitioning the lakes into two distinct clusters associated with lake elevation (Figure 5). As indicated above, the high elevation lakes had significantly different chemistry compared to all other lakes. While this was an interesting result, it overshadowed the influence of water chemistry on cyanobacteria blooms. For this reason, the high elevation lake samples (Upper/Lower Bagley Lakes, Upper/Lower Twin Lakes, Picture Lake and Canyon Lake) were removed from the data set and the data were re-clustered. Although the water chemistry patterns in the high elevation lakes would be an interesting study, the sample size is currently too small to make strong statements about the relationship between algae and water chemistry in these lakes. Based on my observations, the Institute for Watershed Studies will attempt to collect additional high elevation lake data during 2010.

All of the low elevation lakes can be described as warm, shallow and predominantly monomictic, meaning that the lakes usually do not freeze during the winter and are mixed (turned over) once a year (Wetzel 2001). When the hierarchical clustering was repeated without the high elevation lakes, the lakes again separated into two clusters based on differences in water chemistry (Figure 6, Tables 10-11). The lakes in Cluster #2 had higher levels for almost all water chemistry variables compared to Cluster #1 (Table 11). Conductivity and alkalinity appear to contribute strongly to the separation of the two clusters (Table 11), with lakes in Cluster #1 having low alkalinities and conductivities.

In general, lakes that were sampled repeatedly (i.e., more than one year) usually had temporally-stable cluster membership. For example, Wiser Lake was sampled three times

(2007, 2008, 2009), and always clustered into the same group (Cluster #2, Table 10). Only four lakes were in different clusters in different years: Bug, Reed, Squires and Toad Lakes. This clustering inconsistency appeared to have been based on differences in the ammonia, total nitrogen, chlorophyll and total phosphorus concentrations between years (Table 12). Based on these results, I determined that the lakes could be grouped based on water chemistry. In general lake chemistry was temporally stable from year to year (Wetzel 2001, Smith et al. 2006).

Hypothesis #2: Phosphorus will be an important water chemistry parameter that is associated with phytoplankton blooms and chemical features in the lakes.

More than half of all the lake samples were above the state phosphorus goal of 20 µg-P/L (Washington State legislature, 173-201A-230, 2006), suggesting that algae blooms will be a common occurrence, regardless of whether the algal community is dominated by cyanobacteria (Downing et al. 2001). This is valuable information for policy makers and indicates that regular monitoring of small lakes is needed to protect the public from harmful algal blooms (Smith and Schindler 2009). To test if phosphorus levels could classify the lakes two multivariate clustering methods (Kmeans and nonmetric clustering) were tried as well as principal components analysis (PCA) based on ordination. These analyses were used to look for relationships among lake samples categorized as having high or low phosphorus levels. I repeated these tests using high and low chlorophyll categories because of the close correlation between phosphorus and chlorophyll in the lake data (Figure 4). To avoid bias, the chlorophyll data were excluded from the analyses when working with the chlorophyll

categorical groups, and total phosphorus data were excluded when working with the phosphorus categorical groups.

The phosphorus groups were significantly associated with the Kmeans clusters (Figure 7, Table 13; Chi-squared d.f. = 17.023, p-value$\leq$ 0.001), as were the chlorophyll groups (Figure 8, Table 13; Chi-squared d.f. = 20.99, p-value$\leq$ 0.001). Low chlorophyll lakes were mostly in Kmeans Cluster #1 and high chlorophyll lakes were split between both Kmeans clusters (Table 13). Low phosphorus lakes were all in Kmeans Cluster #1 and high phosphorus lakes were split between both Kmeans clusters (Table 13). Similarly, the non-metric clusters were significantly associated with chlorophyll groups (Figure 9, Table 14) and phosphorus groups (Figure 10, Table 14). The most influential water chemistry variables in Kmeans and non-metric clustering were essentially the same as for the cyanobacteria cluster results except that chlorophyll and total phosphorus were dropped as variables when evaluating related categorical groups (see Hypothesis #3). The four highest PRE scores from non-metric clustering were for alkalinity, conductivity, turbidity and pH (Figures 9-10). The non-metric clustering placed almost all of the high chlorophyll lakes into Cluster #1, with 3 misclassifications; the low chlorophyll groups were split between clusters (Table 14). Similarly, the non-metric clustering placed almost all of the high phosphorus lakes in Cluster #1 and almost all the low phosphorus lakes in Cluster #2 (Figure 10, Table 14). Kmeans and non-metric clustering had significant cluster association with phosphorus and chlorophyll; however, the association between clusters (Kmeans and non-metric) and categorical groups were not accurate enough to use phosphorus or chlorophyll as indicators of cluster association.

I used principal components analysis (PCA) to see whether phosphorus and chlorophyll groups ordinate along a gradient in the water chemistry parameters. Again, chlorophyll was removed when I examined chlorophyll categorical groups and phosphorus was removed when I examined phosphorus groups. Principal components I and II accounted for 55% of the total variance in the data, which suggests good ordination. Each lake sample was plotted by its PC scores, using different plotting characters to show the categorical groups (phosphorus and chlorophyll). There was some evidence of weak ordination by chlorophyll categorical groups (Figure 11) and good ordination by phosphorus categorical groups (Figure 12).

I was able to cluster the lakes into groups with similar water chemistry based on the high/low phosphorus and chlorophyll categorical groups. Similarly, the water chemistry data were weakly ordinated along a gradient that was related to chlorophyll categorical groups and there was good ordination for phosphorus and categorical groups. The well-established pattern of high phosphorous as an indicator of algal blooms is present within this study (e.g., Downing et al. 2001, Havens 2008, Smith and Schindler 2009); however, there are a few lakes with low phosphorous that are cyanobacteria dominated (Havens 2008). In general, the lake samples that had cyanobacteria dominance also had high chlorophyll and high total phosphorus (Figure 18, Appendix 3: Table 17), but because there were samples with high chlorophyll and high phosphorus that did *not* have cyanobacteria blooms (see Hypothesis #3), I could only cluster based on chlorophyll and phosphorus categorical groups, not on the cyanobacteria groups (Figure 18).

Hypothesis #3: The lakes will have unique chemical features that can be used to predict whether lakes are likely to develop cyanobacteria blooms.

Based on hierarchical clustering results, I determined that lakes can be grouped according to water chemistry. I then used Kmeans and non-metric clustering to determine if the water chemistry clusters that separated the lakes were associated with cyanobacteria blooms. Both Kmeans and non-metric clustering require specifying how many clusters one wants, but the clusters are "blind" because there are no pre-determined group memberships used to define the clusters. Instead, the programs cluster the data, and then the clusters are tested for association with *a priori* categorical groups.

Although Kmeans produced two clusters with excellent cluster center separations, the clusters were not strongly associated with cyanobacteria dominance (Figure 13). Lakes that had cyanobacteria blooms were instead split between both Kmeans clusters, and there was no statistical association between Kmeans clusters and cyanobacteria groups (Table 13, Chi-squared = 0.66, p= 0.417). Similarly, there was no significant association between non-metric clustering groups and the cyanobacteria groups (Figure 14, Table 14). The best cluster center separations occurred between chlorophyll, turbidity, nitrate, and total phosphorus, where there was almost an order of magnitude difference between the median values in each Kmeans cluster (Figure 13). The four highest PRE scores from non-metric clustering were for alkalinity, conductivity, turbidity and total phosphorus (Figure 14). As with Kmeans clustering, the presence of high PRE scores suggests strong separation into clusters, but the association analysis revealed that the clusters were not associated with cyanobacteria dominance (Table 13).

I used principal components analysis (PCA) to test whether the chemistry data ordinate along gradients related to cyanobacteria dominance. Principal components I and II collectively accounted for 55% of the total variance in the ordination. The variable loadings placed most of the water chemistry parameters between -0.3 to -0.4 on the PC I axis (Figure 15), with the nutrients (ammonia, soluble reactive phosphate, and total phosphorus) separating from temperature, pH, and dissolved oxygen on PC II. Each lake sample was plotted by its PC scores, using different plotting characters to show the categorical groups. Although the data ordinate, the results were very similar to Kmeans and non-metric clustering results in that there was no clear relationship to cyanobacteria dominance (Figure 16).

Based on my definition of cyanobacteria dominance, I was unsuccessful in clustering or ordinating the water chemistry data in a manner that was associated with cyanobacteria dominance. This was consistent regardless of whether I used Kmeans clustering, non-metric clustering or PCA. In general, lakes that developed phytoplankton blooms had higher chlorophyll concentrations, with more phosphorus and total nitrogen, and higher conductivity, alkalinity and turbidity levels; however, this pattern was not strictly related to the presence of cyanobacteria blooms (consistent with results reported in Dokulil and Teubner 2000, Downing et al. 2001, Smith and Schindler 2009).

One obvious question about the lack of association between cyanobacteria blooms and the local lake water chemistry is whether my definition of cyanobacteria bloom ($\geq$ 50% of algal sample was *Anabaena, Aphanizomenon*, or *Microcystis*) might have affected the results. Currently, there is no consistent definition of what constitutes a cyanobacteria bloom. The lack of a standardized definition of cyanobacteria dominance makes predicting

the onset of a bloom challenging. In general, cyanobacteria blooms are identified "after the fact," when the bloom is already evident. For example, a cyanobacteria bloom can be defined as the presence of thick algal mats or mass fatality of organisms in and around the lakeshore (Perez et al. 2010). The World Health Organization defines a mild bloom as 20,000 cyanobacteria cells per mL, but this definition changes based on the amount of microcystin in the water and the intended water uses (WHO 2003). To check whether my bloom definition altered the results, I compared my initial categories with cyanobacteria cell counts. All lakes I categorized as dominated by cyanobacteria had $\geq$20,000 cyanobacteria cells per mL and all lakes that were classified as not dominated by cyanobacteria had <20,000 cyanobacteria cells per mL, following the definition of the World Health Organization.

Based on the results from previous analyses, it seemed unlikely that linear discriminants would be able to predict cyanobacteria dominance in the individual lakes. However, to test this hypothesis formally, a discriminant model was built using all of the 2007-2008 water chemistry data, and evaluated based on whether it could predict the bloom status of the lakes in 2009 using 2009 chemical data. Not surprisingly, the model had only a 30% success rate predicting the lakes that developed cyanobacterial blooms (Figure 17). This was not high enough for this method to be useful as a predictive management tool. The linear discriminant model was successful in predicting non-cyanobacteria dominant lakes with a much higher accuracy (97.9%).

The poor performance of the linear discriminant model may have been due to the low number of lake samples that were dominated by cyanobacteria each year, but was more likely showing the same pattern as in the clustering and PCA results. Lake samples that were

dominated by cyanobacteria could be high or low in chlorophyll and high or low in phosphorus (usually high in both), but high chlorophyll and phosphorus levels were also associated with other types of algal blooms (Figure 18). These results offer weak support for the hypothesis that phosphorus is a good indicator of the potential for cyanobacteria blooms (Downing et al. 2001, Wetzel 2001, Havens 2008), but demonstrate that phosphorus is not an *exclusive* indicator for cyanobacteria blooms. Instead it is an indicator that there are likely to be algal blooms, which may or may not be dominated by cyanobacteria (Figure 18). Additionally, even though phosphorus could not predict cyanobacteria blooms the Washington State level of $\geq$ 20 µgP/L phosphorus is a good cutoff, very few cyanobacteria blooms had phosphorous levels below 20 µgP/L.

Even though phosphorus and chlorophyll could not be used to predict cyanobacteria blooms accurately, these parameters were good indicators of overall algal biomass, and often contribute to cyanobacteria blooms (Paerl 1988, Carpenter et al. 1998, Reynolds 1998, Wetzel 2001, Smith 2003, Smith and Schindler 2009). Because some cyanobacteria can fix dissolved nitrogen gas and some can store excess phosphorus, cyanobacteria blooms may occur when phosphorus and nitrogen concentrations are relatively low (Dokulil and Teubner 2000). Indeed, a few lakes in the present study had phosphorus concentrations below the cutoff but were nonetheless dominated by cyanobacteria (Appendix 3, Table 17). The results herein further confirm that phosphorus and chlorophyll levels are not unique to cyanobacteria blooms but are broad descriptors of algal blooms (Figure 18).

To isolate the factors leading to the development of cyanobacteria blooms, we need a consistent definition of what constitutes a cyanobacteria bloom. A common definition among scientists and watershed managers could provide a better foundation and

understanding of cyanobacteria blooms. In this study I defined cyanobacteria dominance focusing on densities of *Anabaena, Aphanizomenon,* and *Microcystis*, the three most ubiquitous toxin-forming cyanobacteria (WHO 2003, Paerl 2008, Paul 2008, Smith 2009). This definition did not include other species that form blooms and can produce toxins. For example, in Washington State there is an increase in *Woronichinia naegeliana* (personal communication with Dr. Joan Hardy, WA State Department of Health, August 2010). Until recently this species was considered to be a non-toxic species but is now thought to be toxic (personal communication with Tricia Shoblom, WA State Department of Ecology, February, 2010; personal communication with Dr. Joan Hardy, WA State Department of Health, August 2010). We may need to develop separate definitions for cyanobacteria blooms that are associated with human health issues (e.g., toxicity) from cyanobacteria blooms that have limnological consequences (e.g., lake trophic status).

The lakes in my study that had high phosphorus were some of the most impacted lakes, in terms of the presence of invasive species, heavy metal contamination and human development (personal observation and the Washington State Department of Ecology, 303(d) list, 2008). These factors affect lake systems, and may contribute to cyanobacteria blooms (Smith and Schindler 2009), but were not included in my analyses or model. Including additional factors could improve models and increase the accuracy of predicting cyanobacteria blooms.

Predicting cyanobacteria blooms in local lakes is not a simple process. These blooms are most likely the result of a combination of multiple interactions between water chemistry, lake morphology, watershed features, and other factors (Downing et al. 2001, Wynne et al. 2010). This study did not look at N:P ratios or other possible interactive effects using the

water quality data (Havens et al. 2002). This complexity may explain why most of the models that successfully predict cyanobacteria blooms are site-specific and data intensive. It is possible that including additional parameters such as light availability, lake-basin morphometry, lake depth and lake mixing could help with predicting local cyanobacteria blooms (Dokulil and Teubner 2000, Downing et al. 2001, Havens 2008), but there is no guarantee that a simplistic local model would be effective.

Other Factors to Consider

There are many theories regarding the primary factors that promote cyanobacteria blooms. Nutrient loading is the most widely accepted factor, but there are many possible additional contributors. For example, a study by Wynne et al. (2010) used satellite imagery, meteorological data and field data to predict *Microcystis aeruginosa* blooms in Lake Erie. They found that wind stress (wind stress < 0.05 Pa.) and water temperature (> 19 °C) both significantly contributed to increased bloom formation and persistence and further, light availability (cloud cover) only weakly contributed to bloom persistence (Wynne et al. 2010). The study highlights the importance wind stress can play in bloom formation.

Alternately, work by Karlsson et al. (2009) attribute light availability as a far more impotant limiting factor than nutrients. Their model goes against the nutrient paradigm and challenges what we know about the role of nutrients in ecosystem function (Cole 2009). In their study the production of algae (including cyanobacteria blooms), benthic invertebrates and fish were limited by light availability which was, in turn, controlled by dissolved organic matter in the watershed. They attributed eutrophication and high nutrients (high total phosphorus) as the cause of algal blooms in impacted lakes, but for the low nutrient oligotrophic lakes, light availability was a more important limiting factor in producing

blooms (Karlsson et al. 2009). As more light is added it changes not only the likelihood of a bloom but the assemblage of primary producers and consumers. Under high levels of nutrients, periphyton such as cyanobacteria were able to outcompete phytoplankton, which did well in oligotrophic conditions (Karlsson et al. 2009). Karlsson et al. (2009) credited CDOM or colored dissolved organic matter that flowed into the lakes via surrounding watershed for the low light environment.

In contrast with both nutrient influences and light limitation Wang et al. (2010) found that nutrient availability in combination with zooplankton abundance was predictive in bloom formation (Wang et al. 2010). This study was successful in demonstrating that *Microcystis* blooms only dominated only when zooplankton and nutrients were present. When zooplankton were removed, *Chlorophyta* dominated in lieu of *Microcystis,* regardless of the nutrients added (Wang et al. 2010).

All of these studies help further our current understanding of how cyanobacteria respond to environmental stochasticity. Ultimately, ecosystem responses share some general trends but each lake offers unique attributes that may result in different ecosystem outcomes.

Conclusion

The most important result of this study is that although lakes could be clustered based on water chemistry, it was not possible to predict which lakes would develop cyanobacteria blooms. The strongest clustering in the water chemistry data occurred between low elevation and high elevation lakes. After omitting the atypical high elevation lakes, I found that the remaining low elevation lakes could be described as predominantly shallow, monomictic, and with low alkalinities. These low elevation lakes clustered into two groups that

corresponded to phosphorus and chlorophyll categorical groups. Contrary to conventional assumptions, the phosphorous and chlorophyll groups did not relate to cyanobacteria bloom formation. Furthermore, it was not possible to accurately predict cyanobacteria bloom formation based on water chemistry data using the analyses here.

It is evident from my analyses that predicting cyanobacteria blooms is a challenging management question that affects the future of our water supply. The most critical step for making better predictions would be to identify specific factors that are associated with cyanobacteria blooms as opposed to factors that associated with algal blooms in general. However, based on this study, it appears that simple models based on phosphorous or chlorophyll levels are not likely to yield accurate predictions regarding cyanobacteria blooms. Thus, it is likely that closer monitoring and more comprehensive data sets are necessary if we are to have accurate predictive models of cyanobacteria blooms. Such predictive models are worth developing as they can be used to decrease our response time, and therefore lessen the impact of cyanobacteria blooms on freshwater ecosystems.

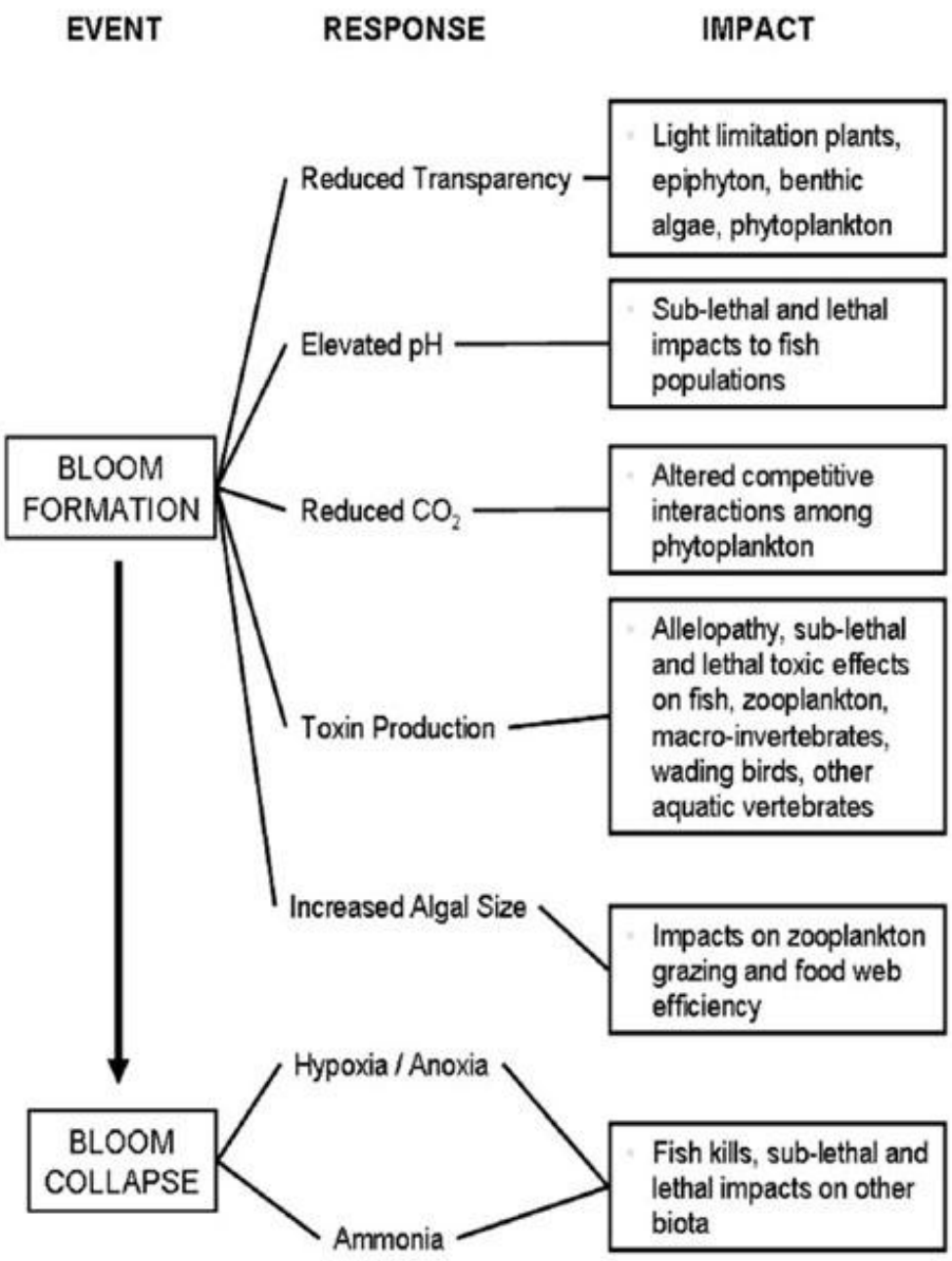


Figure 1. Summary of ecological responses and impacts associated with blooms of cyanobacteria (redrawn with permission, K. Havens, 2008).

Figure 2. Map showing the location of lakes that were sampled by the Institute for Watershed Studies for the small lakes monitoring project, 2007-2009.

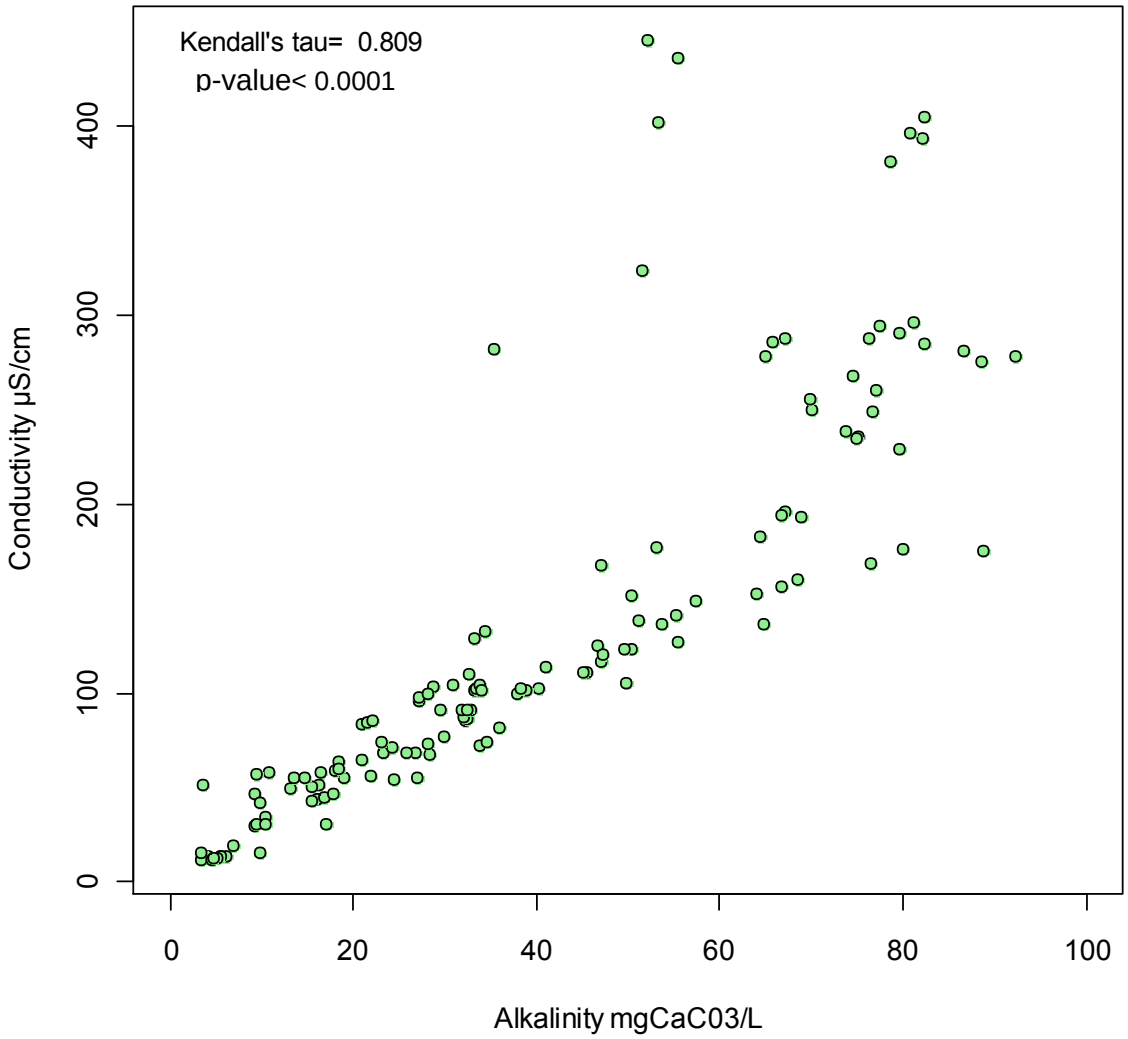


Figure 3. Correlation between alkalinity and conductivity in the lakes sampled by the Institute for Watershed Studies for the small lakes monitoring project, 2007-2009.

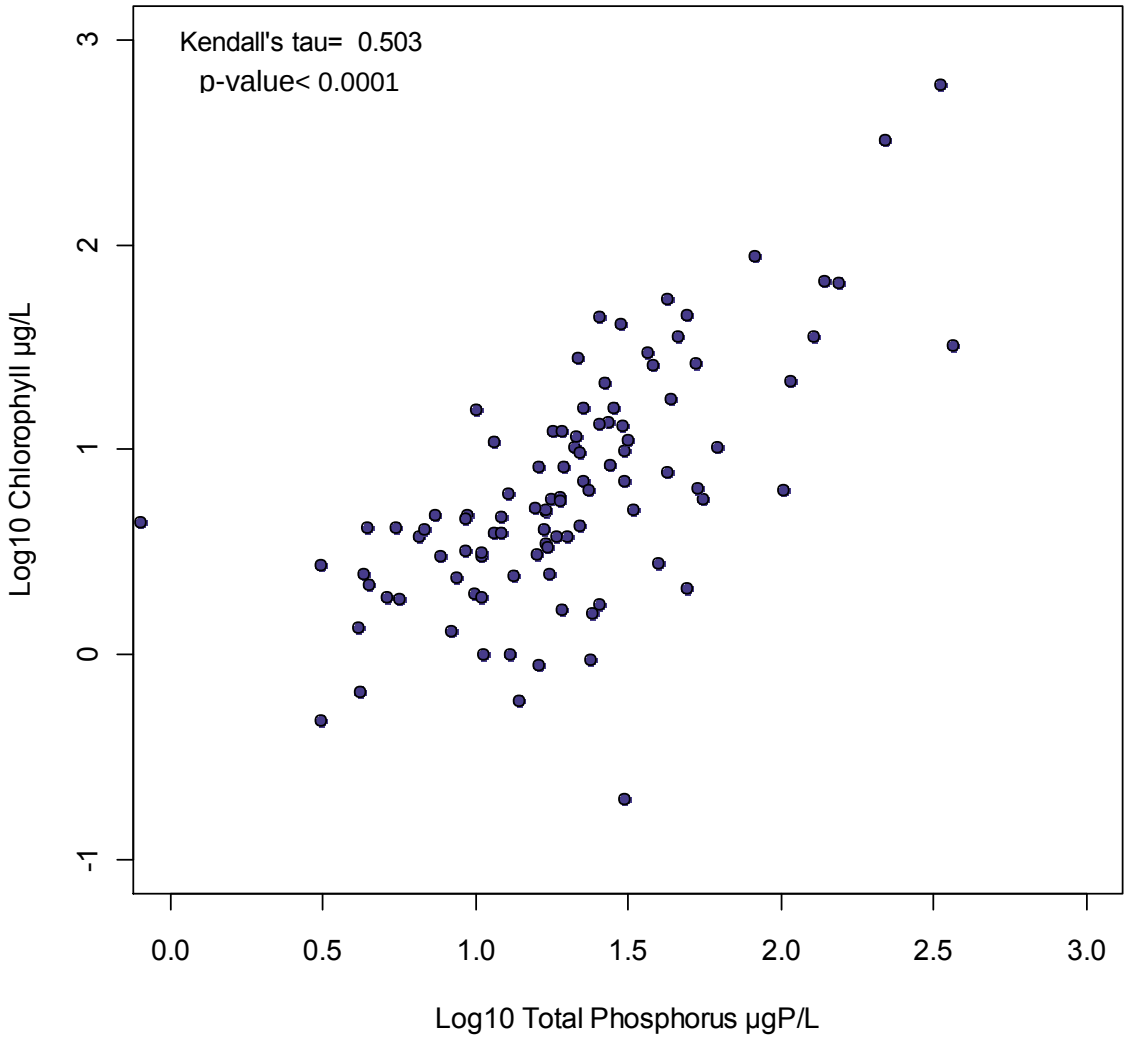


Figure 4. Correlation between chlorophyll and total phosphorus in the lakes sampled by the Institute for Watershed Studies for the small lakes monitoring project, 2007-2009.

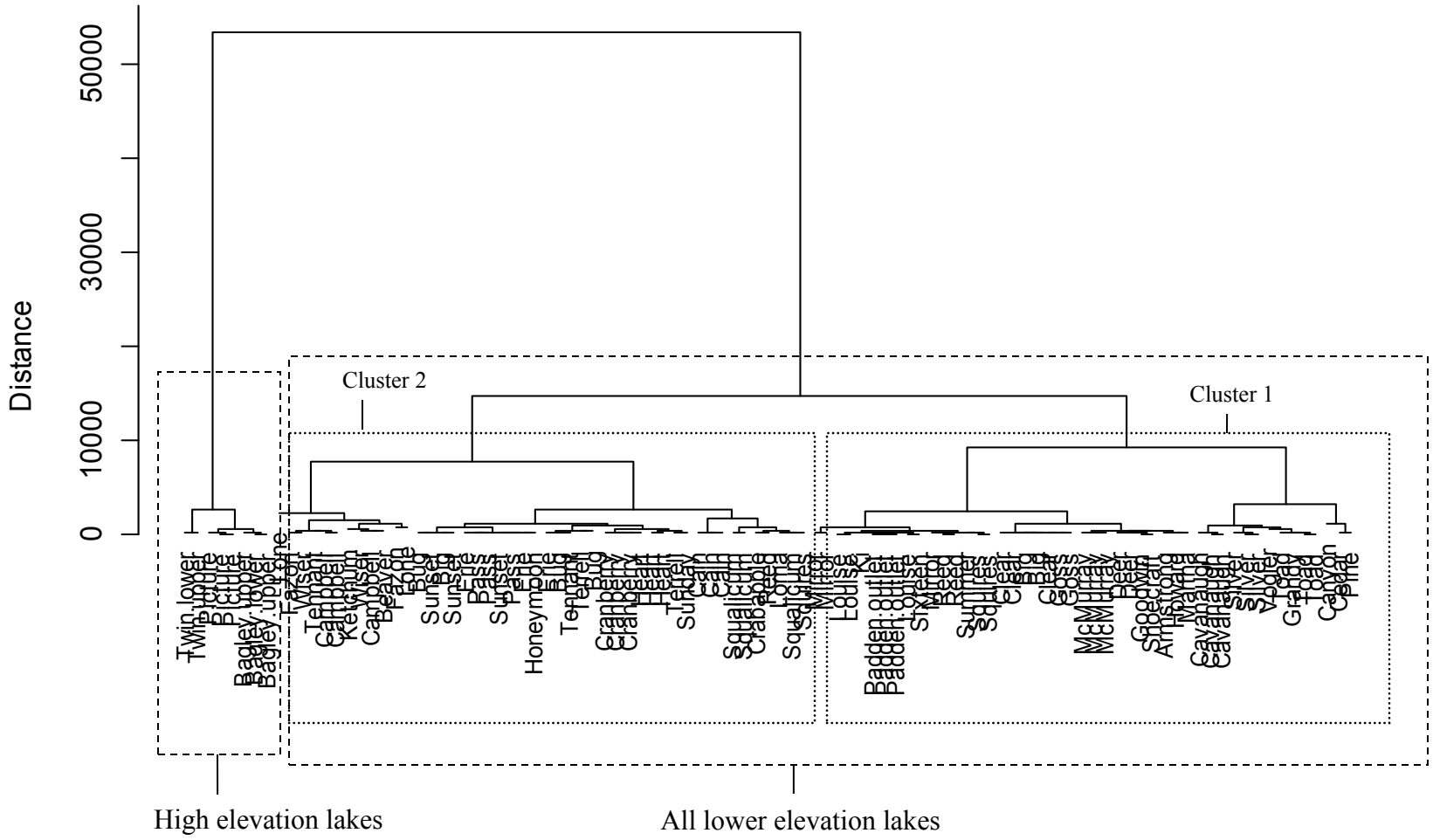


Figure 5. Hierarchical agglomerative clustering results for lake samples (squared Euclidean distance and Ward's clustering method).

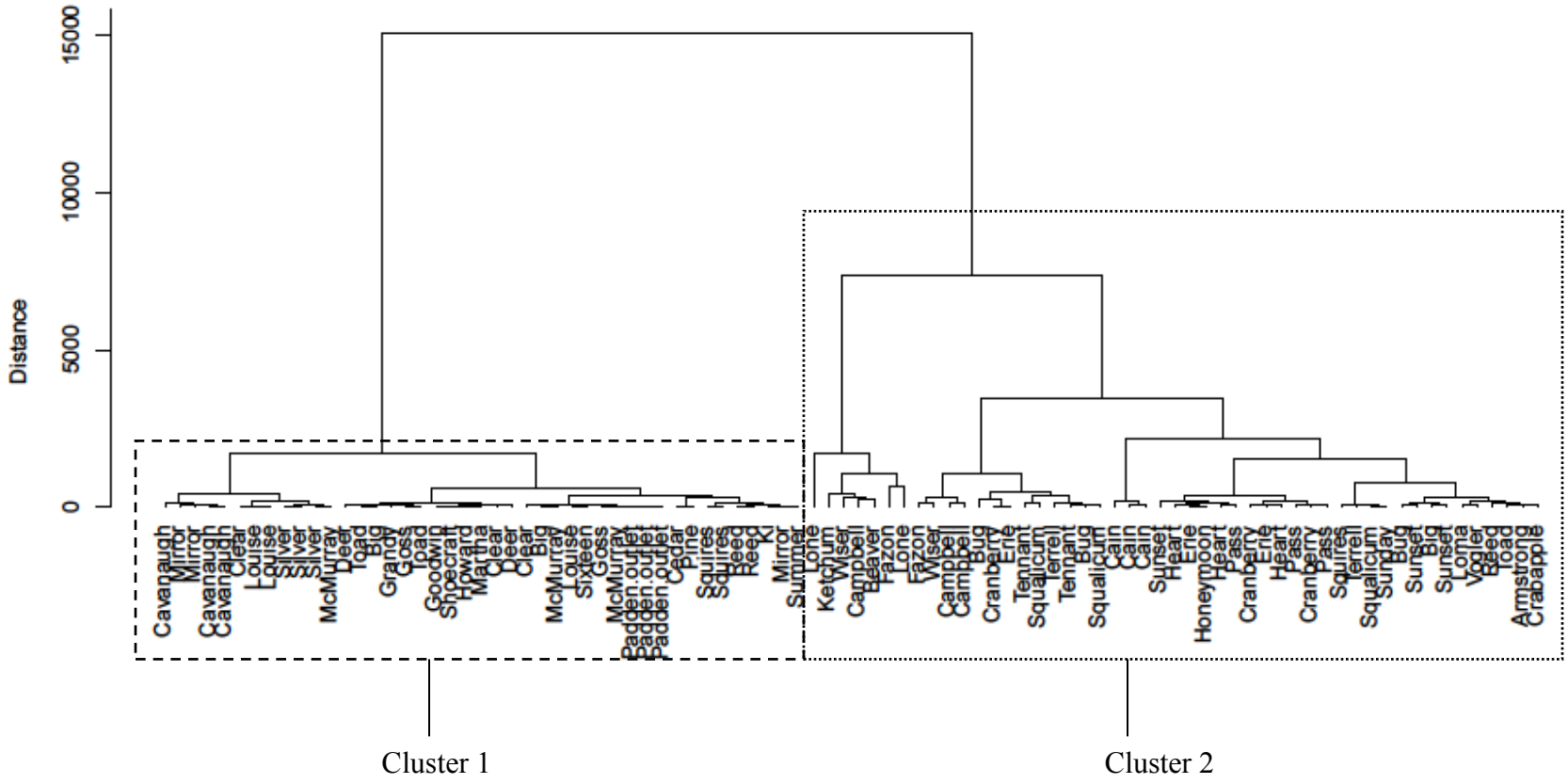
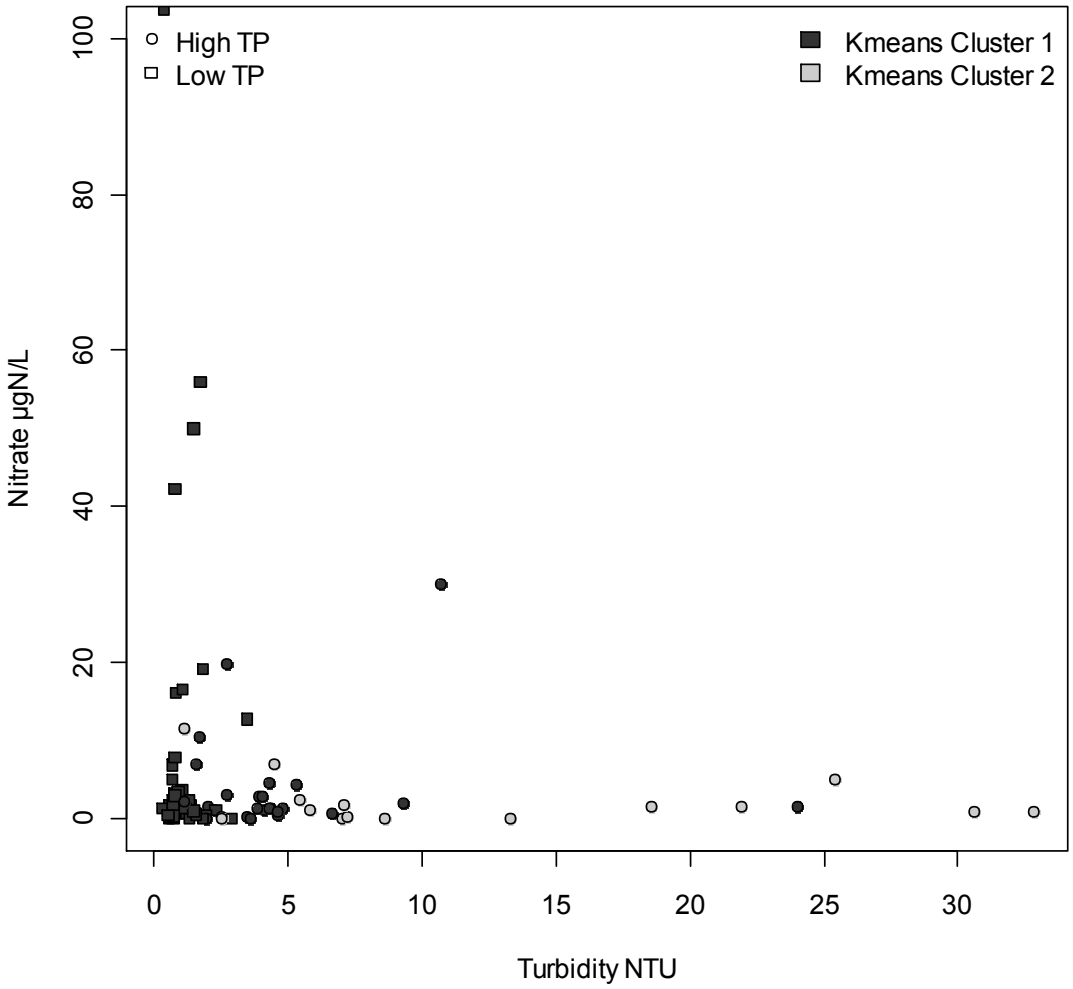


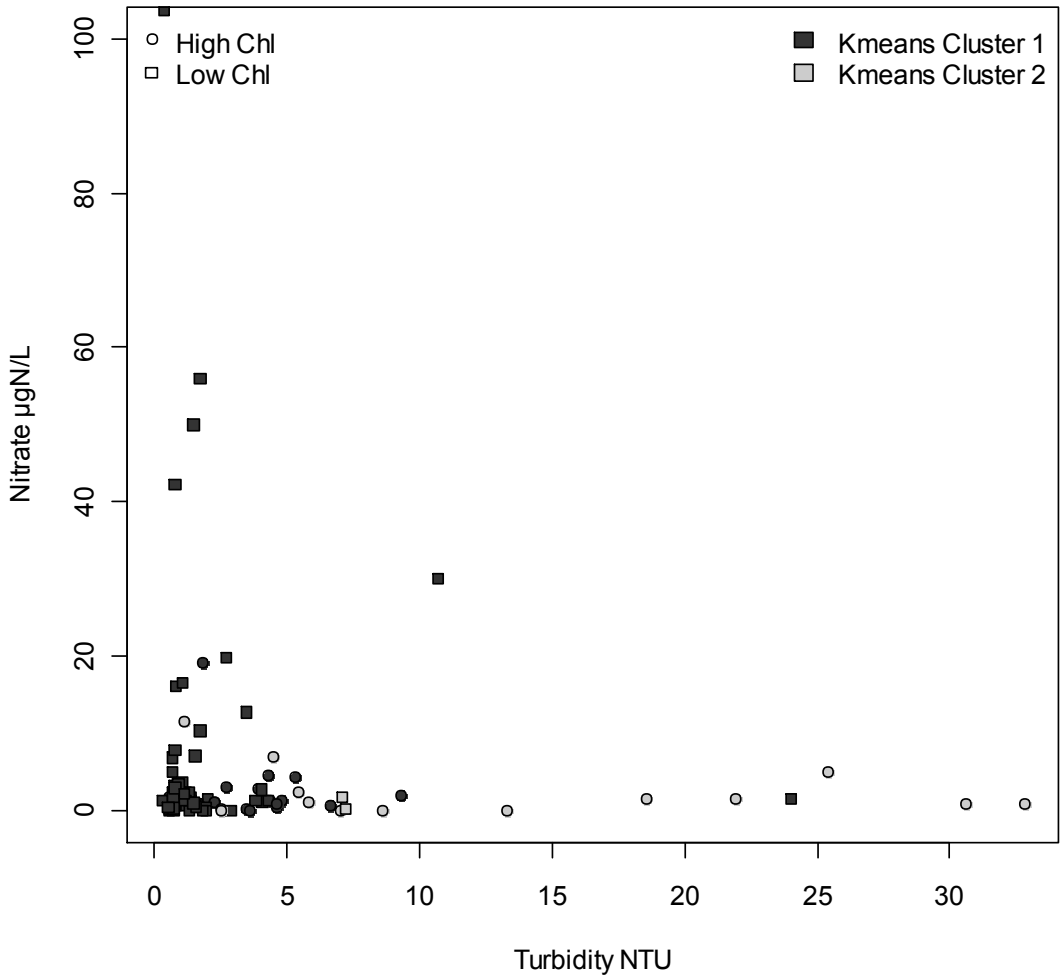
Figure 6. Hierarchical agglomerative clustering for all lake samples with high elevation lakes removed (squared Euclidean distance and Ward's cluster method)



The Kmeans cluster centers. Centers are based on means.

	DO mg/L	Temp (C)	pH	Cond µS/cm	Chl µg/L	Alk $mgCaCO_3/L$	Turb (NTU)
Cluster1	8.77	21.31	8.26	243.06	86.35	62.76	12.16
Cluster2	8.38	20.63	7.83	114.22	8.35	36.82	2.36
	NH_3 µgN/L	TN µgN/L	NO_3 µgN/L	TP µgP/L	SRP µgP/L		
Cluster1	83.99	1412.06	2.18	N/A	33.73		
Cluster2	12.34	506.73	27.71	N/A	4.57		

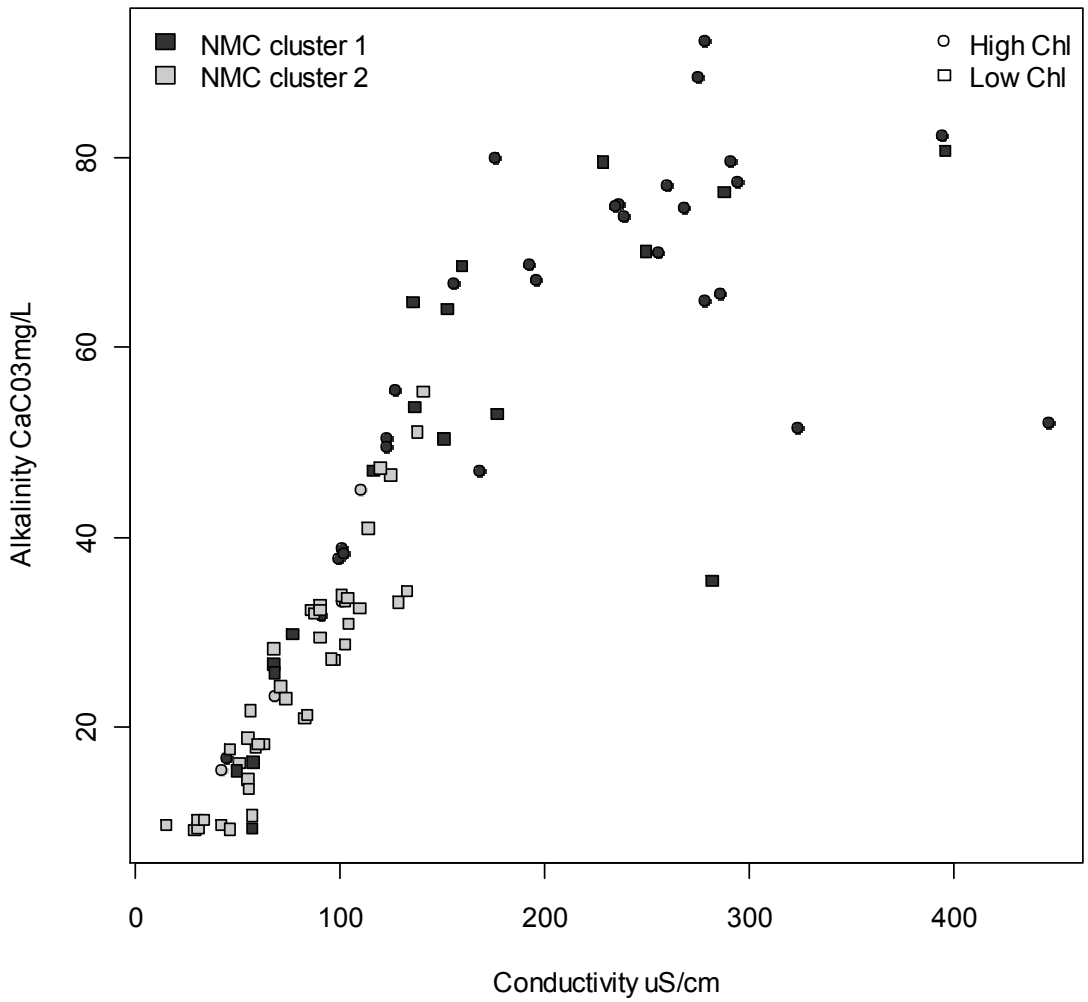
Figure 7. Summary of Kmeans clusters and total phosphorus groups plotted by turbidity and nitrate. All low phosphorus lake samples were all placed in Kmeans Cluster 1, along with 30 of the high phosphorus lake samples.



The Kmeans cluster centers. Cluster centers are based on means.

	DO mg/L	Temp (C)	pH	Cond µS/cm	Chl µg/L	Alk $mgCaCO_3/L$	Turb (NTU)
Cluster 1	8.77	21.31	8.26	243.06	N/A	62.76	12.16
Cluster 2	8.38	20.63	7.83	114.22	N/A	36.82	2.36
	NH_3 µgN/L	TN µgN/L	NO_3 µgN/L	TP µgP/L	SRP µgP/L		
Cluster 1	83.99	1412.06	2.18	121.30	33.73		
Cluster 2	12.34	506.73	27.71	18.63	4.57		

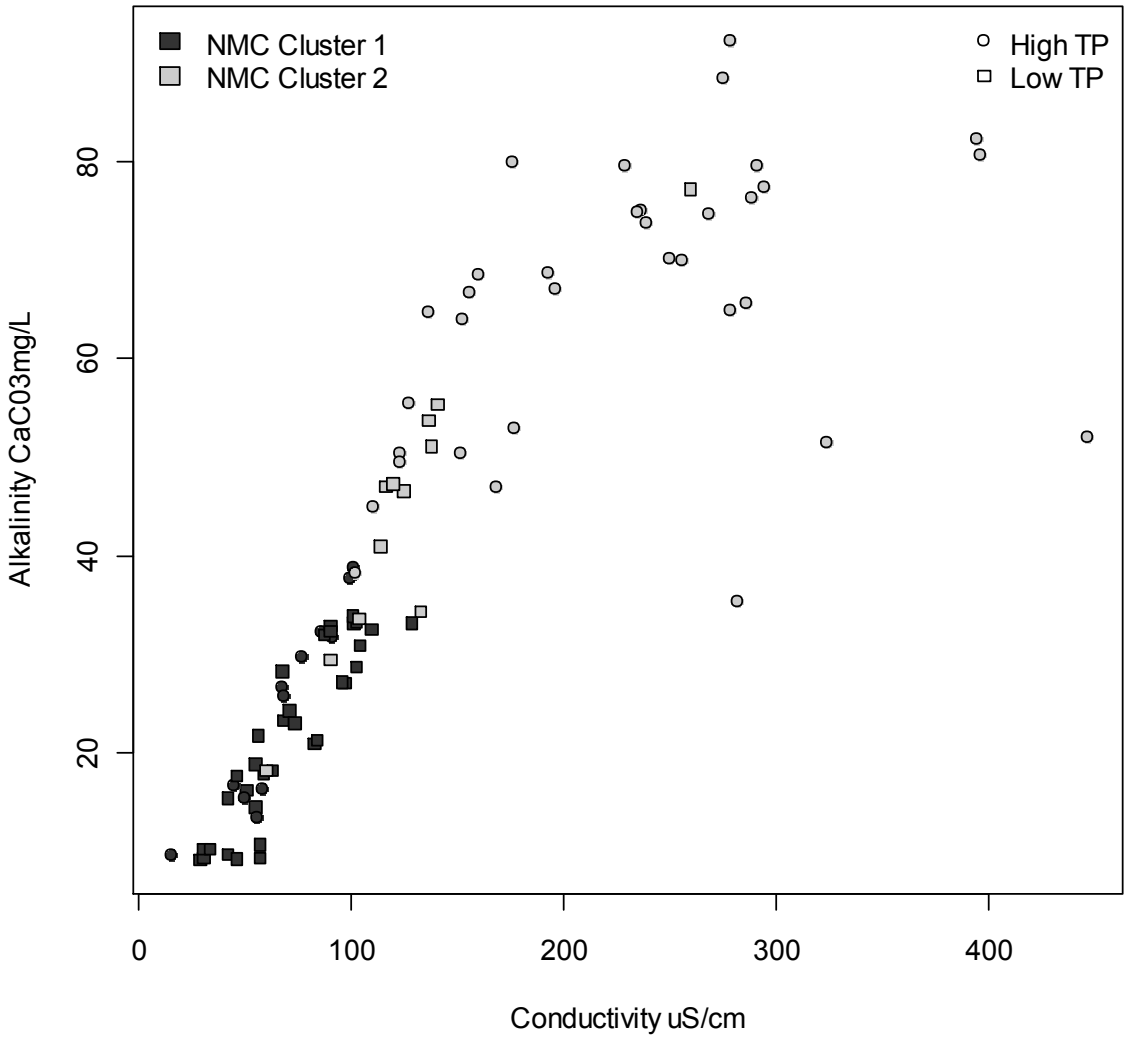
Figure 8. Summary of Kmeans clusters and chlorophyll groups plotted by turbidity and nitrate. All but two low chlorophyll lakes were in Cluster 1; high chlorophyll lakes were split between both Kmeans clusters.



Chlorophyll PRE Scores; boldface PRE scores were the best predictors.

DO mg/L	Temp (C)	**pH**	**Cond µS/cm**	**Alk $mgCaCO_3/L$**	**Turb (NTU)**
0.30	0.10	**0.61**	**0.87**	**0.91**	**0.57**
NH_3 µgN/L	TN µgN/L	NO_3 µgN/L	TP µgP/L	SRP µgP/L	Chl µg/L
0.0	0.39	0.23	0.52	0.19	N/A

Figure 9. Summary of non-metric clusters and chlorophyll groups plotted by alkalinity and conductivity. Non-metric cluster runs yielded consistent results (10/10 runs)



Total Phosphorus PRE Scores; boldface PRE scores were the best predictors.

DO mg/L	Temp (C)	**pH**	**Cond µS/cm**	Chl µg/L	**Alk $mgCaCO_3/L$**
0.30	0.14	**0.61**	**0.87**	0.45	**0.91**
Turb (NTU)	NH_3 µgN/L	TN µgN/L	NO_3 µgN/L	TP µgP/L	SRP µgP/L
0.57	0.04	0.43	0.23	N/A	0.14

Figure 10. Summary of non-metric clusters and total phosphorus groups plotted by alkalinity and conductivity. Non-metric cluster runs yielded consistent results (10/10 runs)

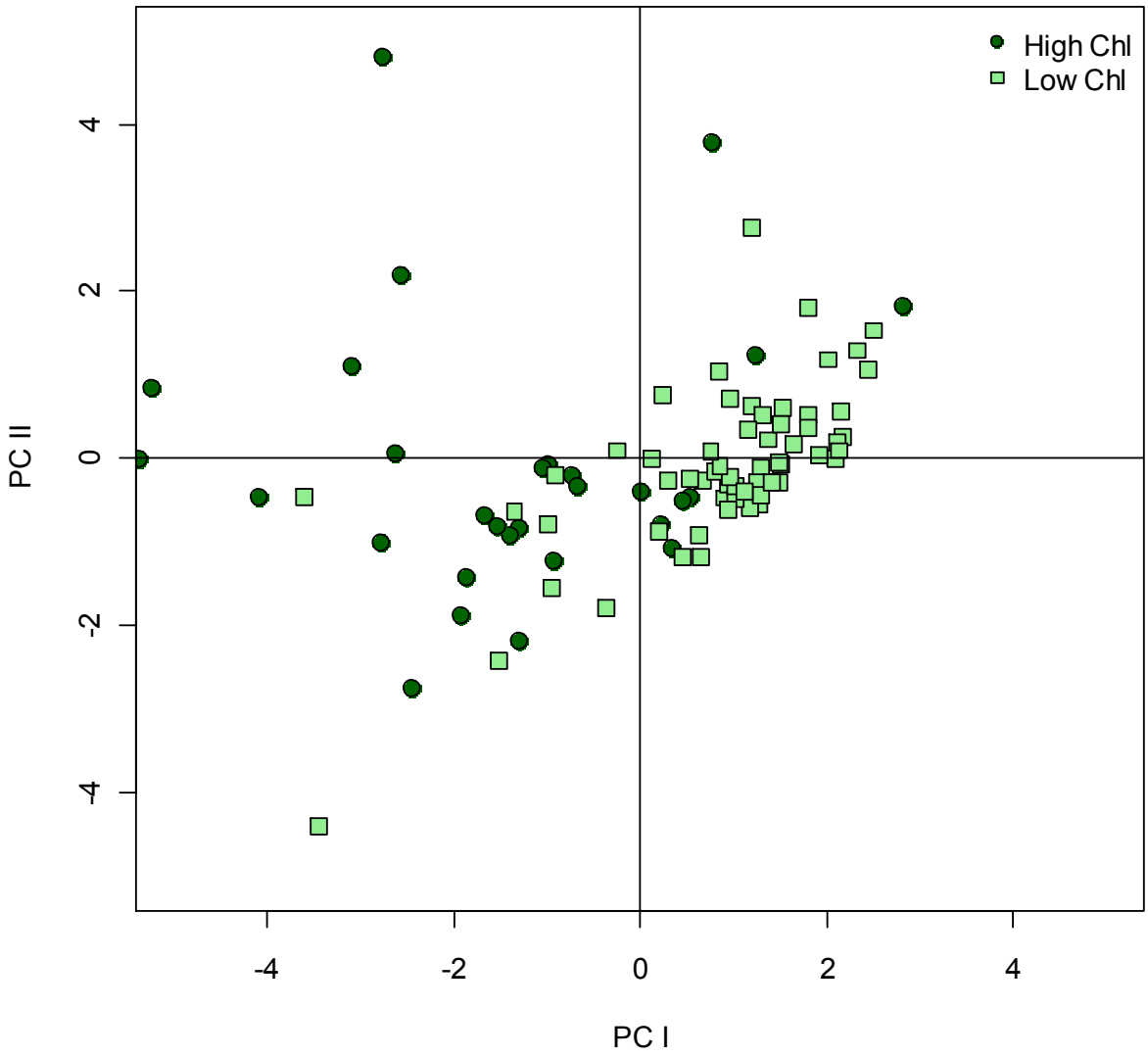


Figure 11. Principal components ordination of the lake samples showing chlorophyll categorical groups (chlorophyll omitted as a response variable).

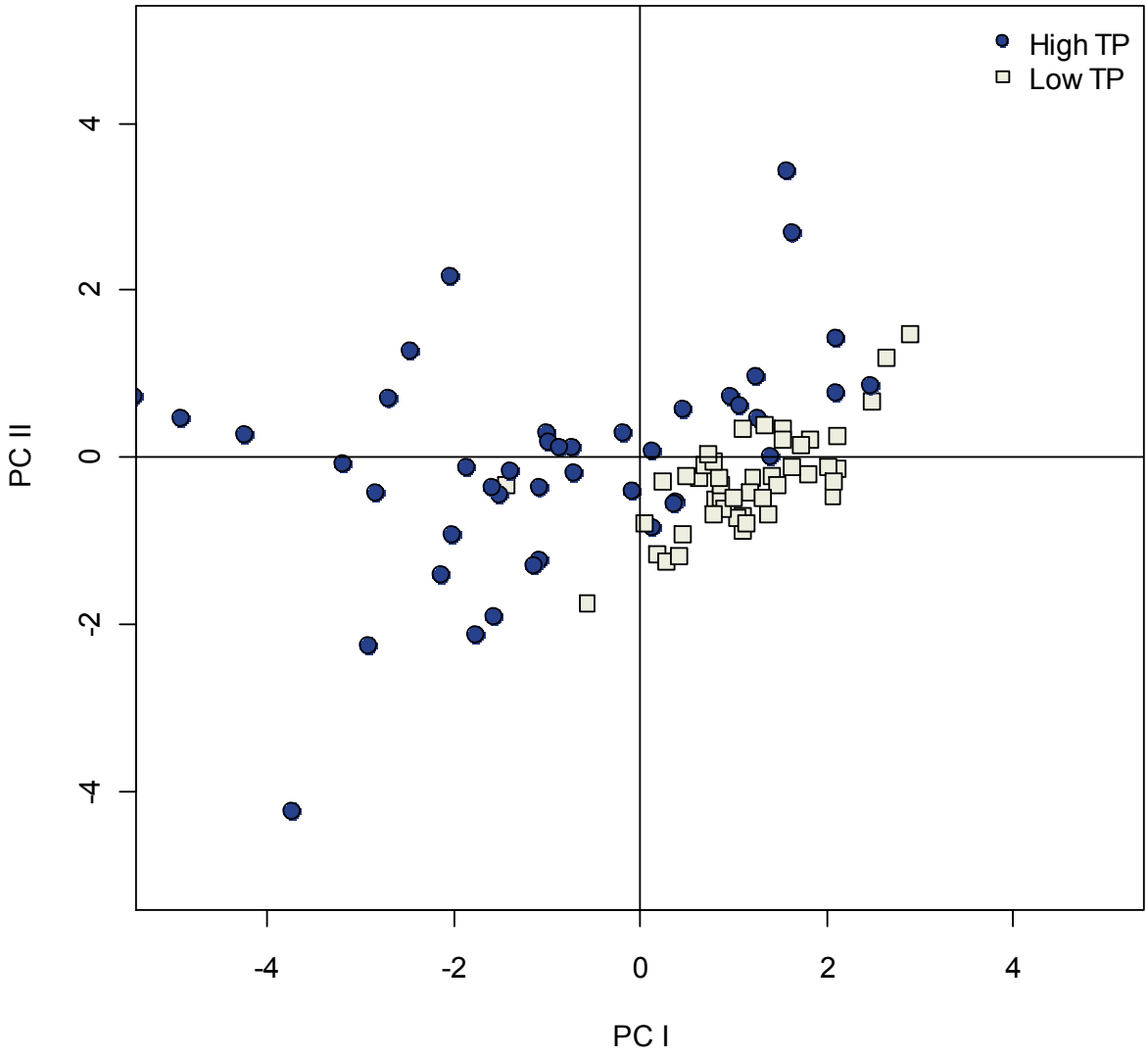
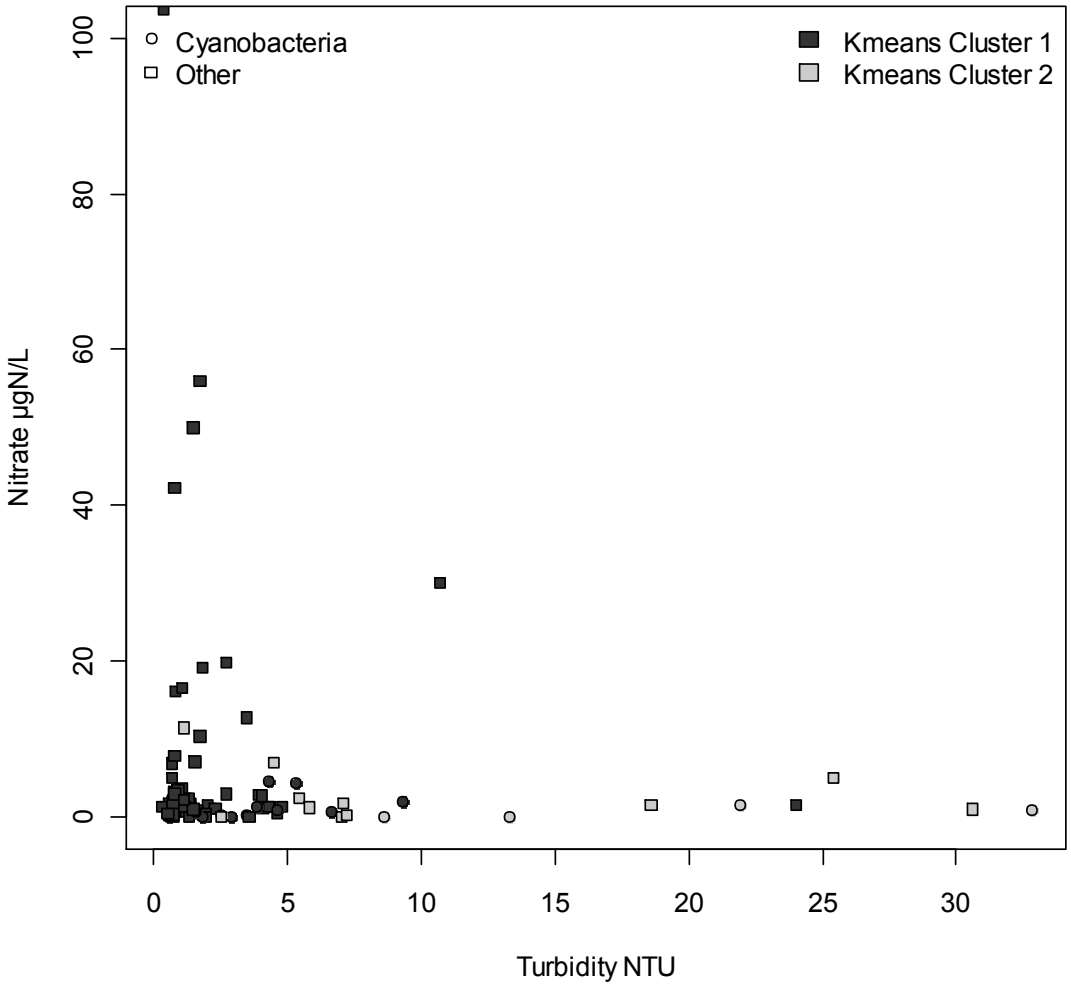


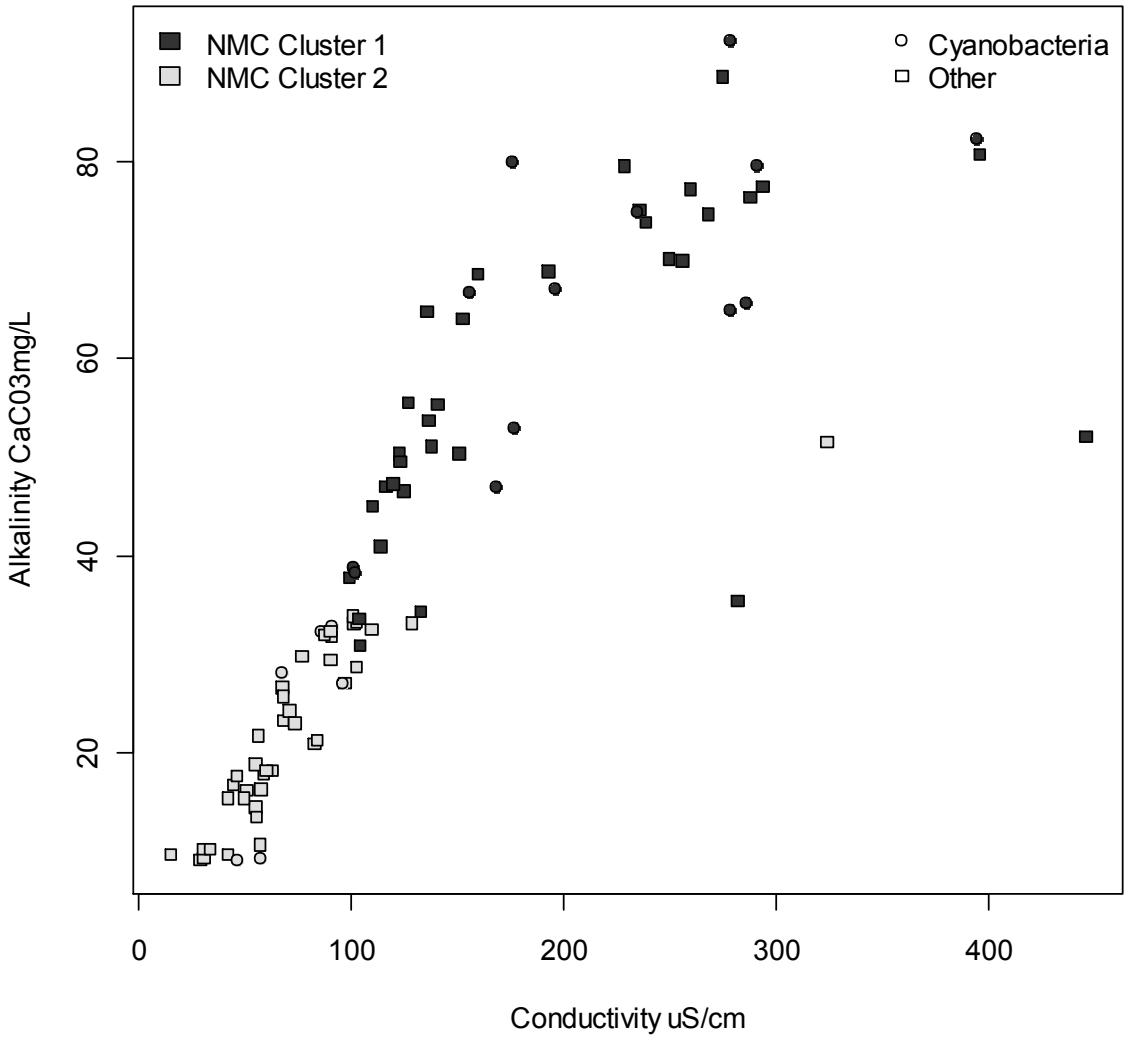
Figure 12. Principal components ordination of the lake samples showing phosphorus categorical groups (total phosphorus omitted as a response variable).



The Kmeans cluster centers. Centers are based on means.

	DO mg/L	Temp (C)	pH	Cond µS/cm	Chl µg/L	Alk $mgCaCO_3/L$	Turb (NTU)
Cluster 1	8.77	21.31	8.26	243.06	86.35	62.76	12.16
Cluster 2	8.38	20.63	7.83	114.22	8.35	36.82	2.36
	NH_3 µgN/L	TN µgN/L	NO_3 µgN/L	TP µgP/L	SRP µgP/L		
Cluster 1	83.99	1412.06	2.18	121.30	33.73		
Cluster 2	12.34	506.73	27.71	18.63	4.57		

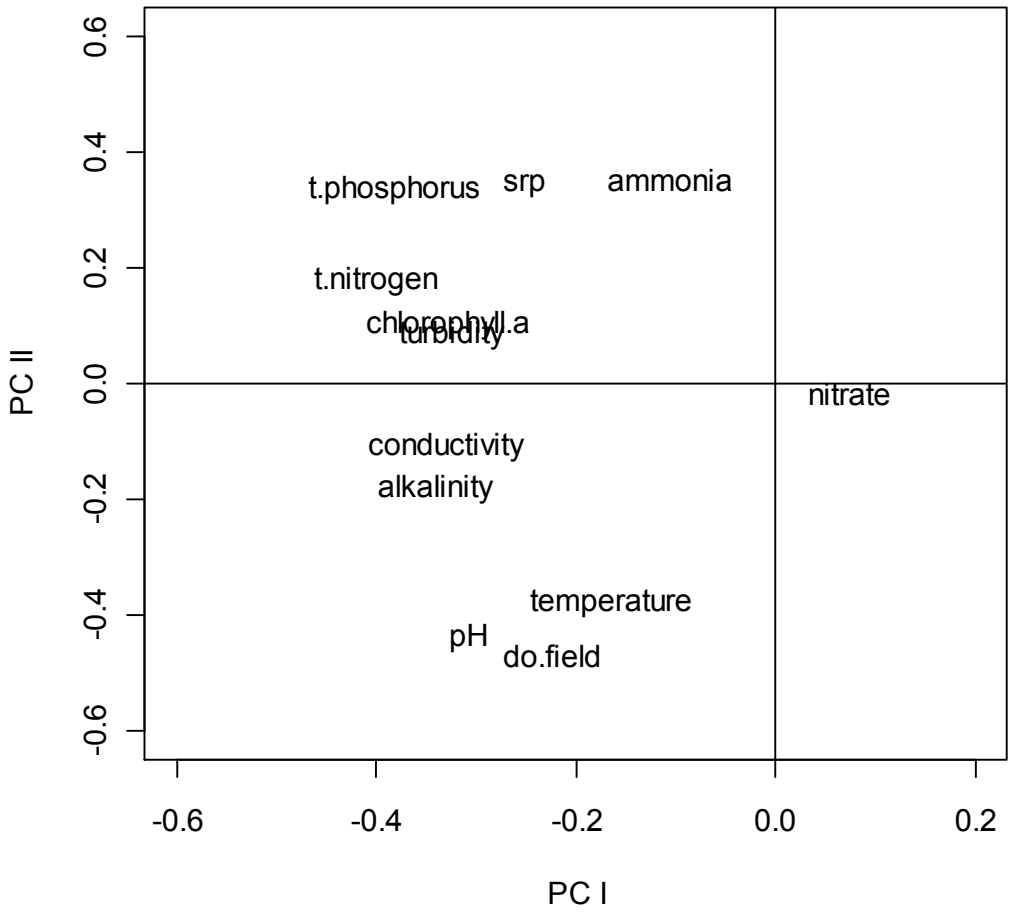
Figure 13. Summary of Kmeans clusters and cyanobacteria dominance groups plotted by turbidity and nitrate.



Cyanobacteria PRE Scores; boldface PRE scores were the best predictors

DO mg/L	Temp (C)	pH	**Cond µS/cm**	Chl µg/L	**Alk $mgCaCO_3/L$**
0.23	0.10	0.43	**0.74**	0.49	**0.83**
Turb (NTU)	NH_3 µgN/L	TN µgN/L	NO_3 µgN/L	**TP µgP/L**	SRP µgP/L
0.70	0.09	0.57	0.14	**0.70**	0.27

Figure 14. Summary of non-metric clusters and cyanobacteria dominance groups plotted by alkalinity and conductivity. Non-metric cluster runs yield consistent results (9/10 runs).



PCA	PC1	PC2	PC3	PC4	PC5	PC6
Standard deviations:	2.12	1.45	1.19	1.08	0.95	0.84
Proportion of Variance	0.37	0.18	0.12	0.10	0.08	0.06
Cumulative Proportion	0.37	0.55	0.67	0.77	0.84	0.90
Eigenvalue	4.44	2.16	1.44	1.20	0.96	0.72

PCA cont.	PC7	PC8	PC9	PC10	PC11	PC12
Standard Deviations:	0.67	0.56	0.43	0.35	0.31	0.18
Proportion of Variance	0.04	0.03	0.02	0.01	0.01	0.00
Cumulative Proportion	0.94	0.96	0.97	0.98	0.99	1.00
Eigenvalue	0.48	0.36	0.24	0.12	0.12	0.00

Figure 15. Principal components variable loading scores for the water chemistry data.

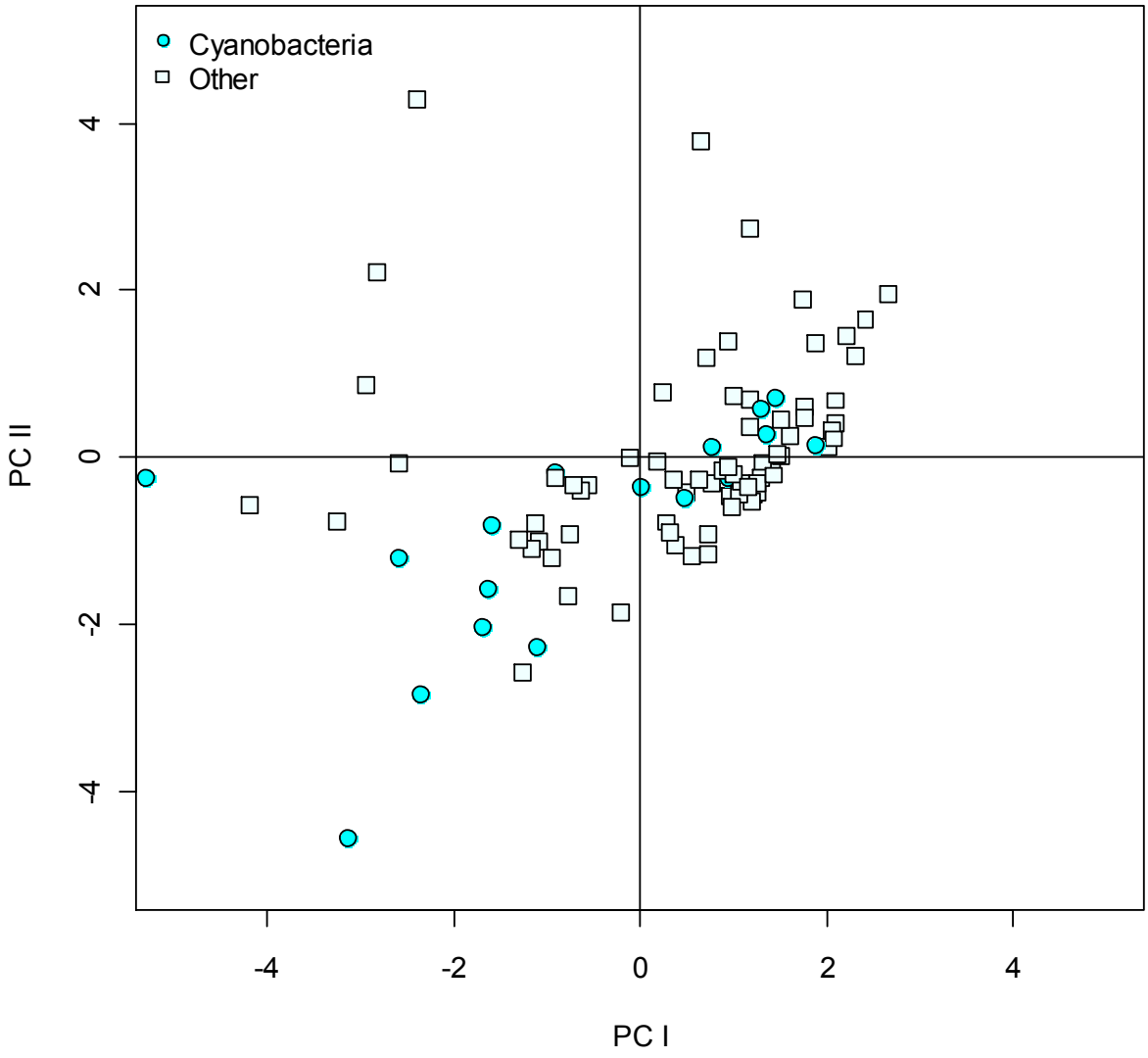


Figure 16. Principal components ordination of the lake samples based on water chemistry showing algal dominance groups.

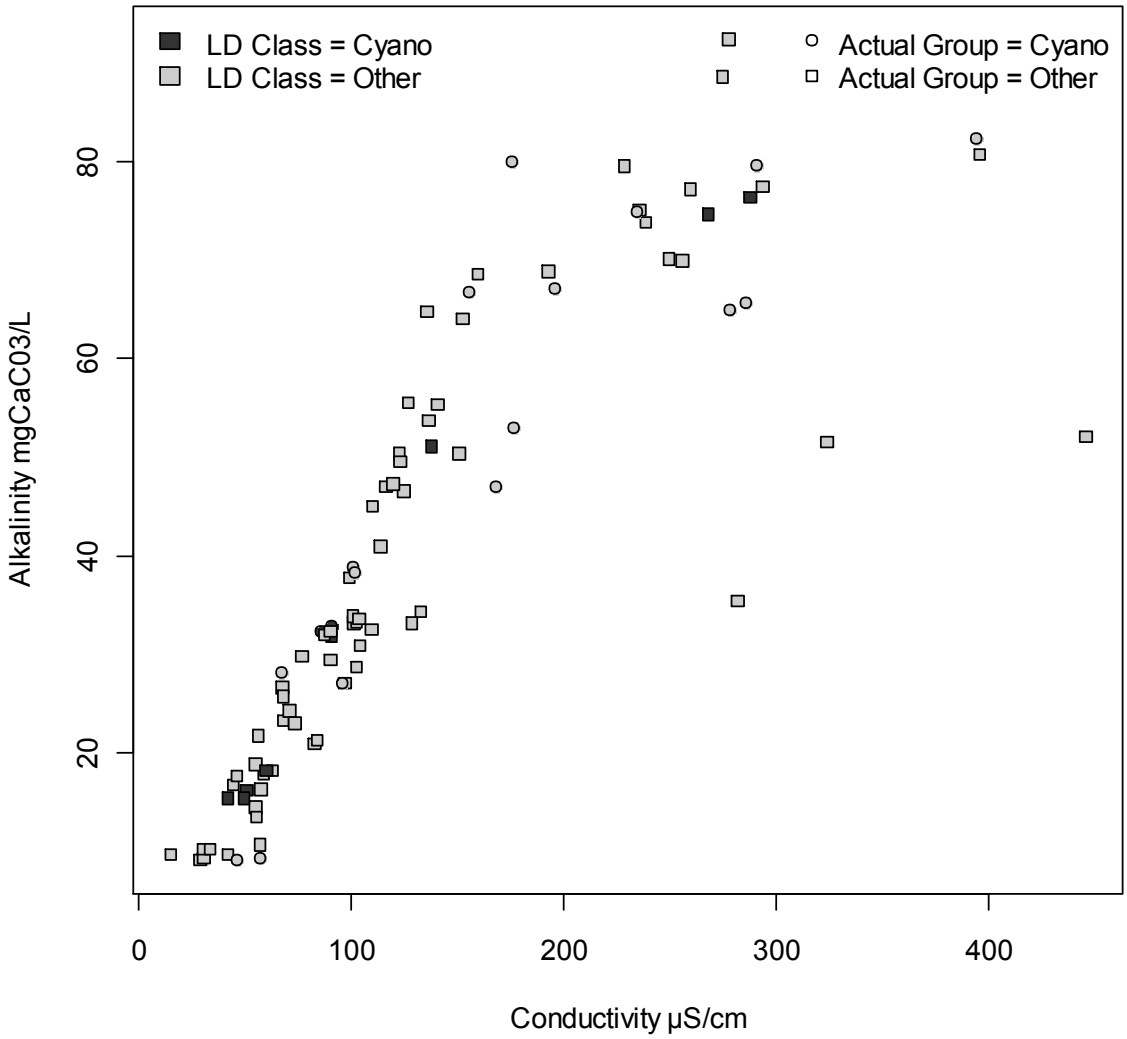


Figure 17. Linear discriminant ordination of the 2009 IWS small lakes samples based on a model built from the 2007-2008 data.

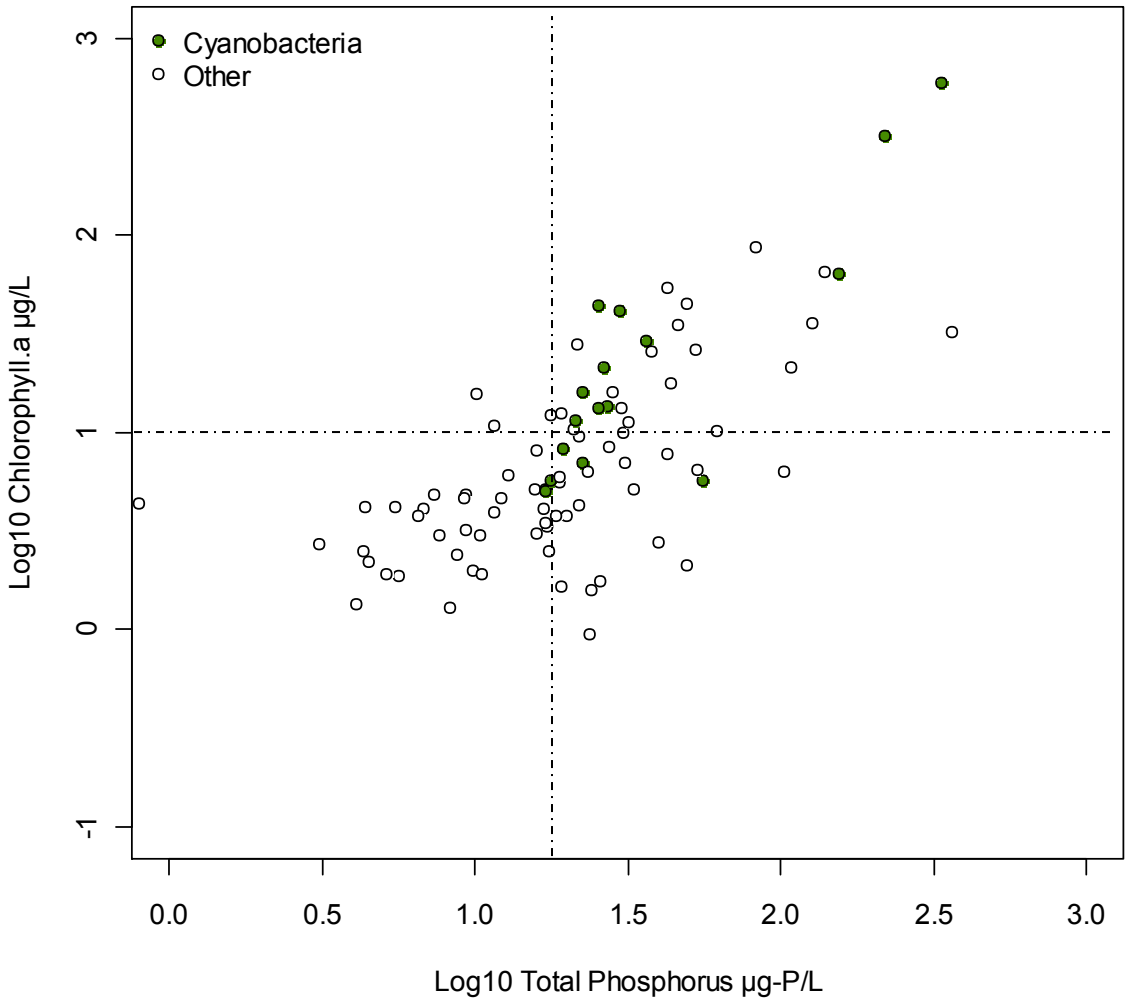


Figure 18. The lake samples graphed with algal groups. The lakes are plotted by chlorophyll and phosphorus. High chlorophyll and high phosphorus are usually indicative of algal blooms, including cyanobacteria blooms. Dashed lines represent 10 µg/L chlorophyll and 20 µgP/L phosphorus

Table 1. Summary of toxins known to occur in cyanobacteria within Washington lakes. Toxicity can only be determined through molecular analysis.

Genera	Toxin	Type of Toxin
*Anabaena**	anatoxin-a, anatoxin-a(s), saxitoxin, microcystins	neurotoxins
*Microcystis**	microcystins	hepatotoxin
*Aphanizomenon**	saxitoxin, neosaxitoxin	neurotoxins
*Gloeotrichia**	microcystins, lipopolysaccharides	hepatotoxin, cytotoxins
*Woronichinia**	currently being researched	hepatotoxin
*Oscillitoria**	microcystins	hepatotoxins
*Nostoc**	microcystins	hepatotoxins
Planktothrix	microcystins	hepatotoxins
*Lyngbya**	microcystins, saxitoxins, aplysiatoxins, lyngbyatoxins,	hepatotoxins, cytotoxins
Cylindrospermopsis	saxitoxin, neosaxitoxin	neurotoxins

* Reported in the 2007-2009 IWS plankton counts. Toxin information from WHO, 2003.

Table 2. Lakes sampled as part of the Institute for Watershed Studies small lakes monitoring project.

Lake	Year	County	Lake	Year	County
Armstrong	2009	*Snohomish*	Lone	2008-09	*Island*
Bagley lower	2007-08	*Whatcom*	Louise	2007-09	*Whatcom*
Bagley upper	2007-08	*Whatcom*	Martha	2009	*Snohomish*
Beaver	2009	*Skagit*	McMurray	2007-09	*Skagit*
Big	2007-09	*Skagit*	Mirror	2007-09	*Whatcom*
Bug	2007-09	*Whatcom*	Padden	2007-09	*Whatcom*
Cain	2007-09	*Whatcom*	Pass	2007-09	*Skagit*
Campbell	2007-09	*Skagit*	Picture	2007-09	*Whatcom*
Canyon	2007-08	*Whatcom*	Pine	2008	*Whatcom*
Cavanaugh	2007-09	*Skagit*	Reed	2007-09	*Whatcom*
Cedar	2008	*Whatcom*	Shoecraft	2009	*Snohomish*
Clear	2007-09	*Skagit*	Silver	2007-09	*Whatcom*
Crabapple	2009	*Snohomish*	Sixteen	2009	*Skagit*
Cranberry	2007-09	*Island*	Squalicum	2007-09	*Whatcom*
Deer	2008-09	*Island*	Squires	2007-09	*Skagit/Whatcom*
Erie	2007-09	*Skagit*	Summer	2009	*Skagit*
Fazon	2007-09	*Whatcom*	Sunday	2009	*Snohomish*
Goodwin	2009	*Snohomish*	Sunset	2007-09	*Whatcom*
Goss	2007-09	*Island*	Tennant	2007-08	*Whatcom*
Grandy	2009	*Skagit*	Terrell	2007-08	*Whatcom*
Heart	2007-09	*Skagit*	Toad	2007-09	*Whatcom*
Honeymoon	2009	*Island*	Twin lower	2007-08	*Whatcom*
Howard	2009	*Snohomish*	Twin upper	2007-08	*Whatcom*
Ketchum	2009	*Snohomish*	Vogler	2009	*Skagit*
Ki	2009	*Snohomish*	Wiser	2007-09	*Whatcom*
Loma	2009	*Snohomish*			

Table 3. Summary of analytical methods and detection limits used by the Institute for Watershed Studies for the small lakes monitoring project

Parameter	Method Reference	Detection Limit (dl) or Sensitivity (+)	Abbreviation
Dissolved Oxygen – YSI	SM4500-O G, Membrane electrode	±0.1 mg/L	DO
Temperature- YSI	SM2550 Thermistor	±0.1 C	Temp (C)
Chlorophyll α	10200 H, Acetone	NA	Chl
Alkalinity	SM2320, Titration	±0.5 mg $CaCO_3$/L	Alk
Turbidity	SM2130, Nephelometric	±0.2 NTU	Turb
pH	SM4500-H, Electrometric	±0.1 units	pH
Conductivity	SM2510, Meter	±0.1 units µS/cm	Cond
Ammonia	SM4500-NH3 H, Flow injection analysis, phenate	10 µg NH_3-N/L	NH_3
Total Persulfate Nitrogen	M4500-NO3 I, persulfate digestion and flow injection analysis	10 µg N/L	TN
Nitrate + Nitrite	SM4500-NO3 I, flow injection analysis, cadmium reduction	10 µg NH_3-N/L	NO_3
Total Phosphorus	SM4500-P G, persulfate digestion and flow injection analysis	5 µg P/L	TP
Soluble Reactive Phosphorus	SM4500-P G, flow injection analysis	3 µg PO_4-P/L	SRP

Method Reference: APHA. 1998 Standard Methods for Examination of Water and Wastewater, 20th Edition. American Public Health Association, American Water Works, and Water Environment Federation, Washington, DC. Information acquired from the Institute for Watershed Studies (IWS), 2010.

Table 4. Unique algal taxa identified and counted for the Institute for Watershed Studies's small lakes monitoring project 2007-2009.

***Genus* (± species)**	**Group**	**Code in Data File**
Anabaena Bory de Saint-Vincent ex Bornet & Flahault	bluegreen	anabaena
Aphanizomenon A. Morren ex Bornet et Flahault	bluegreen	aphanizomenon
Aphanocapsa Nägeli	bluegreen	aphanocapsa
Filamentous unknown bluegreen	bluegreen	bluegreen.fil
Chroococcus Nägeli	bluegreen	chroococcus
Eucapsis Clements & Shantz	bluegreen	eucapsis
Gloeocapsa Kützing	bluegreen	gloeocapsa
Gloeotrichia echinulata (J.E. Smith) P. Richter C	bluegreen	gloeotrichia.echinulata
Gomphosphaeria Kützing	bluegreen	gomphosphaeria
Lyngbya C.Agardh ex Gomont	bluegreen	lyngbya
Merismopedia Meyen	bluegreen	merismopedia
Microcystis aeruginosa Kützing	bluegreen	microcystis
Oscillatoria Vaucher ex Gomont	bluegreen	oscillatoria
Phormidium Kützing ex Gomnt	bluegreen	phormidium
Pseudanabaena Lauterborn	bluegreen	pseudanabaena
Snowella lacustris Elenkin	bluegreen	snowella
Spirulina Turpin ex Gomont	bluegreen	spirulina
Woronichinia naegeliana (Unger) Elenkin	bluegreen	woronichinia
Bitrichia Woloszynska	chrysophyte	bitrichia
Chrysamoeba G.A. Klebs	chrysophyte	chrysamoeba
Chrysosphaerella longispina Lauterborn	chrysophyte	chrysosphaerella
Dinobryon Ehrenberg	chrysophyte	dinobryon
Epipyxis C.C. Ehrenberg	chrysophyte	epipyxis
Mallomonas Perty	chrysophyte	mallomonas
Mallomonas akrokomos Ruttner C	chrysophyte	mallomonas.akro
Dinobryon –sessile unknown	chrysophyte	sessile.dinobryon
Single celled chrysophyte	chrysophyte	ss.chrysophyte
Synura Ehrenberg	chrysophyte	synura
Synuropsis J. Schiller	chrysophyte	synuropsis
Uroglena americana Calkins	chrysophyte	uroglena
Cryptomonas C.G. Ehrenberg	cryptophyte	cryptomonas
Komma caudata (L. Geitler) D.R.A. Hill C	cryptophyte	komma.chroomonas
Chroomonas Hansgirg	cryptophyte	komma.chroomonas
Closterium Nitzsch ex Ralfs	desmid	closterium
Cosmocladium Brébisson	desmid	cosmocladium
Desmid	desmid	desmid
Diatoms	diatom	diatoms
Urosolenia F.E. Round & R.M. Crawford	diatom	urosolenia
Ceratium hirundinella (O.F. Müller) Dujardin	dinoflagellate	ceratium

Table 4. continued

***Genus* (± species)**	**Group**	**Code in Data File**
Ceratium furcoides (Levander) Langhans P	dinoflagellate	ceratium furcoides
Cystodinium Klebs	dinoflagellate	cystodinium
Dinoflagellates	dinoflagellate	dinoflagellates
Gymnodinium Stein	dinoflagellate	gymnodinium
Peridinium C.G. Ehrenberg	dinoflagellate	peridinium
Peridinium inconspicuum Lemmermann	dinoflagellate	peridinium inconsp
Euglena Ehrenberg	euglenoid	euglena
Phacus Durjardin	euglenoid	phacus
Trachlomonas C.G. Ehrenberg	euglenoid	trachelomonas
Ankistrodesmus Corda	green	ankistrodesmus
Ankyra Fott	green	ankyra
Ankyra ancora Fott	green	ankyra.ancora
Botryococcus Kützing	green	botryococcus
Bulbochaete C. Agarhd	green	bulbochaete
Chlamydomonas C.G. Ehrenberg	green	chlamydomonas
Chlorella M. Beijerinck	green	chlorella
Crucigenia Morren	green	crucigenia
Crucigeniella Lemmermann	green	crucigeniella
Dictyosphaerium pulchellum H.C. Wood	green	dictyosphaerium
Elakatothrix gelatinosa Wille	green	elakatothrix
Eudorina elegans Ehrenberg	green	eudorina
Gloeocystis Nägeli	green	gloeocystis
Golenkinia radiata Chodat	green	golenkinia
Kirchneriella Schmidle	green	kirchneriella
Lagerheimia R. Chodat	green	lagerheimia
Micractinium Fresinius	green	micractinium
Microspora Thuret	green	microspora
Monoraphidium Komárková-Lengnerová	green	monoraphidium
Mougeotia C. Agardh	green	mougeotia
Nephrocytium Nägeli	green	nephrocytium
Oocystis A. Braun	green	oocystis
Pandorina mora (O.F. Müller) Bory de Saint-Vincent	green	pandorina
Paradoxia multiseta Svirenko	green	paradoxia
Pediastrum Meyen	green	pediastrum
Pediastrum tetras (Ehrenberg) Ralfs	green	pediastrum.tetras
Planktosphaeria G.M. Smith	green	planktosphaeria
Pleodorina californica W.R. Shaw	green	pleodorina
Quadrigula chodatii (Tanner-Füllemann) G.M. Smith	green	quadrigula
Scenedesmus Meyen	green	scenedesmus
Selenastrum Reinsch	green	selenastrum

Table 4. continued

***Genus* (± species)**	**Group**	**Code in Data File**
Sphaerocystis schroeteri R. Chodat	green	sphaerocystis
Spirogyra Link	green	spirogyra
Single celled green	green	ss.green
Tetraedron Kützing	green	tetraedron
Tetraspora lacustris Lemmermann	green	tetraspora.lacustris
Treubaria C. Bernard	green	treubaria
Colonial green	green	colonial.green
Unknown colonial	green	unk.colonial

Table 5. Summary of algal dominance in the lakes sampled by the Institute for Watershed Studies (2007-2009). Lakes that were dominated by cyanobacteria are identified using an open circle (○) and lakes that were dominated by other types of algae are identified using an asterisk (*). In cyanobacteria-dominated lakes, if the majority of the counts (≥ 50%) were collectively from *Anabaena, Aphanizomenon,* and *Microcystis*, the lake is identified using a filled circle (●).

Lake	2007	2008	2009	Lake	2007	2008	2009
Armstrong	-	-	●	Lone	-	*	●
Bagley lower	*	*	-	Louise	○	○	○
Bagley upper	*	*	-	Martha	-	-	○
Beaver	-	-	○	McMurray	○	○	○
Big	○	●	●	Mirror	*	*	*
Bug	*	○	●	Padden	○	○	○
Cain	○	○	○	Pass	●	○	○
Campbell	○	○	●	Picture	○	*	*
Canyon	*	*	-	Pine	-	*	-
Cavanaugh	○	○	○	Reed	*	*	*
Cedar	-	○	-	Shoecraft	-	-	○
Clear	●	○	●	Silver	*	○	*
Crabapple	-	-	○	Sixteen	-	-	○
Cranberry	●	○	●	Squalicum	*	○	*
Deer	-	○	○	Squires	*	*	○
Erie	○	*	○	Summer	-	-	*
Fazon	*	○	○	Sunday	-	-	●
Goodwin	-	-	○	Sunset	●	*	●
Goss	*	○	○	Tennant	*	○	-
Grandy	-	-	○	Terrell	○	○	-
Heart	*	○	●	Toad	○	○	○
Honeymoon	-	-	○	Twin lower	*	*	-
Howard	-	-	○	Twin upper	*	*	-
Ketchum	-	-	●	Vogler	-	-	*
Ki	-	-	●	Wiser	●	○	●
Loma	-	-	●				

Table 6. Summary of algal categorical groups. Kruskal-Wallis pair-wise tests were done for each parameter in the water chemical data set by cyanobacteria dominance group.

	Alk* $mgCaCO_3/L$	DO** mg/L	Temp** (C)	pH*	Cond* µS/cm	Chl*** µg/L
Cyanobacteria n=19	53.0	9.8	21.1	8.5	168.0	13.6
Other n=73	33.2	8.2	20.3	7.8	102.6	4.7

	Turb** (NTU)	NH_3 µgN/L	TN** µgN/L	NO_3** µgN/L	TP* µgP/L	SRP µgP/L
Cyanobacteria n=19	3.9	7.7	752.0	0.9	25.4	4.6
Other n=73	1.4	10.6	449.0	1.8	18.4	3.8

Median significant difference using Kruskal-Wallis chi squared test: *p-value≤ 0.05, **p-value≤ 0.01, ***p-value≤ 0.001.

Table 7. Summary of high and low chlorophyll groups. Kruskal-Wallis pair-wise tests were done for each parameter in the water chemical data set by chlorophyll group.

	Alk* $mgCaCO_3/L$**	**DO mg/L**	**Temp** (C)**	**pH****	**Cond*** µS/cm**	**Chl*** µg/L**
High Chl n=32	65.4	9.3	21.1	8.5	194.5	23.6
Low Chl n=60	29.2	8.2	20.5	7.7	89.2	4.0

	Turb* (NTU)**	**NH_3µgN/L**	**TN*** µgN/L**	**NO_3µgN/L**	**TP*** µgP/L**	**SRP*** µgP/L**
High Chl n=32	4.6	9.1	858.6	1.2	34.1	6.2
Low Chl n=60	1.1	10.3	424.1	1.8	16.4	3.5

High chl= high chlorophyll ≥ 10 µg/L, low chl = low chlorophyll ≤10 µg/L.
Median significant difference at *p-value≤ 0.05, ** p-value≤ 0.01, *** p-value≤ 0.001, Kruskal-Wallis chi-squared test.

Table 8. Summary of high and low total phosphorus groups. Kruskal-Wallis pair-wise tests were done for each parameter in the water chemical data set by phosphorus group.

Group	Alk*** $mgCaCO_3/L$	DO mg/L	Temp (C)	pH *	Cond*** µS/cm	Chl*** µg/L
High TP n=46	59.8	8.7	20.9	8.3	171.9	13.3
Low TP n=46	27.2	8.2	20.6	7.7	85.9	3.9

	Turb*** (NTU)	NH_3 µgN/L	TN*** µgN/L	NO_3µgNL	TP*** µgP/L	SRP*** µgP/L
High TP n=46	4.3	9.6	779.9	1.4	32.4	5.7
Low TP n=46	0.8	10.3	389.6	1.8	10.3	3.5

High tp = high phosphorus $\geq$ 20µgP/L, and low tp = low phosphorus $\leq$ 20µgP/L. Median significant difference at *p-value$\leq$ 0.05, **p-value$\leq$ 0.01, ***p-value$\leq$ 0.001, Kruskal-Wallis chi-squared test.

Table 9. Comparison between high and low elevation lake samples in the small lakes project. The high elevation group was removed from the analyses due to unique chemistry. This will be further investigated in the summer of 2010 by the Institute for Watershed Studies.

	Elev. * Feet**	**DO * mg/L**	**Temp*** (C)**	**pH *****	**Cond *** µS/cm**	**Chl *** µg/L**
High elevation n=15	4334	9	12.6	7.1	13.8	1.0
Low elevation n=120	275	8.3	20.8	7.9	104.6	5.7

	Alk* $mgCaCO_3/L$**	**Turb*** (NTU)**	**NH_3*** µg N/L**	**TN*** µg N/L**	**$N0_3$** µgN/L**	**TP*** µgP/L**	**SRP** µg P/L**
High elevation n=15	5.6	0.5	3.9	76.5	4.6	12.2	1.3
Low elevation n=120	36.9	1.7	9.7	554.9	2.2	20.1	3.8

Median significant difference at *p-value≤ 0.05, **p-value≤ 0.01, ***p-value≤ 0.001, Kruskal-Wallis chi-squared test.

Table 10. Summary of the hierarchical clustering groups by lake (high elevation lakes excluded). Only four lakes had samples that were split between cluster groups for different years.

Cluster 1	Year	Cluster 2	Year
Cavanaugh	2007-09	Armstrong	2009
Cedar	2008	Beaver	2009
Clear	2007-09	Big	2007-09
Deer	2008-09	Cain	2007-09
Goodwin	2009	Campbell	2007-09
Goss	2007-09	Crabapple	2009
Grandy	2009	Cranberry	2007-09
Howard	2009	Erie	2007-09
Ki	2009	Fazon	2007-09
Louise	2007-09	Heart	2007-09
Martha	2009	Honeymoon	2009
McMurray	2007-09	Ketchum	2009
Mirror	2007-09	Loma	2009
Padden	2007-09	Lone	2008-09
Pine	2008	Pass	2007-09
Shoecraft	2009	Squalicum	2007-09
Silver	2007-09	Sunday	2009
Sixteen	2009	Sunset	2007-09
Summer	2009	Tennant	2007-08
		Terrell	2007-08
		Vogler	2009
		Wiser	2007-09

Lakes that split between the two clusters

Cluster 1		Cluster 2	
Bug	2007	Bug	2008-09
Reed	2007-08	Reed	2009
Squires	2007,2009	Squires	2008
Toad	2007	Toad	2008-09

Table 11. Hierarchical clustering statistics (medians) for Cluster 1, Cluster 2. Cluster 2 is higher in dissolved oxygen, temperature, pH, conductivity, alkalinity, turbidity, total nitrogen, and total phosphorus.

Year	Cluster	DO mg/L	Temp (C)	pH	Cond µS/cm	Chl µg/L	Alk $mgCaCO_3/L$
Cluster 1	median	8.2	20.5	7.6	89.2	3.9	29.9
	mean	8.0	20.3	7.6	84.7	5.5	28.4
Cluster 2	median	8.6	20.9	8.3	169.9	10.3	52.6
	mean	8.8	21.1	8.2	180.2	35.7	52.2

		Turb (NTU)	NH_3 µgN/L	TN µgN/L	NO_3 µgN/L	TP µgP/L	SRP µgP/L
Cluster 1	median	1	9.3	358.2	1.7	11	3.4
	mean	2.07	10.51	339.45	10.16	12.91	3.61
Cluster 2	median	3.1	10.1	817.4	1.4	30.3	5.2
	mean	5.74	36.81	936.95	34.27	56.29	14.71

Table 12. Hierarchical clustering statistics for lakes split between clusters.

	Year	Cluster	DO mg/L	Temp (C)	pH	Cond µS/cm	Chl µg/L	Alk $mgCaCO_3/L$
Bug	2007	1	11.6	24.2	9.3	159.7	4.3	68.5
Bug	2008	2	5.1	22.2	9.1	123.2	25.75	49.6
Bug	2009	2	21.5	25.3	10.5	177	5.7	53
Reed	2007	1	8.2	19.7	7	55.2	2.5	18.9
Reed	2008	1	7.8	21.3	7.5	51.1	3.34	16.3
Reed	2009	2	5.6	18.8	6.8	50	2.8	15.5
Split 1			**8.0**	**20.1**	**7.3**	**53.2**	**4.2**	**18.3**
Split 2			**7.4**	**22.3**	**8.7**	**118.3**	**5.8**	**47.2**
Squires	2007	1	2.7	19.8	6.1	42.5	15.7	15.5
Squires	2009	1	3	19.7	6.6	46.3	4.1	17.7
Squires	2008	2	6.4	20.3	6.9	44.7	54.6	16.8
Toad	2007	1	9.7	20.3	8.5	110.5	15.9	45
Toad	2008	2	8.4	22.4	8.2	116.6	4.65	47
Toad	2009	2	10.3	22.8	9.1	120	5.9	47.3

	Year	Cluster	Turb (NTU)	NH_3 µgN/L	TN µgN/L	NO_3 µgN/L	TP µgP/L	SRP µgP/L
Bug	2007	1	2.0	9.5	658.6	1.5	21.8	3.2
Bug	2008	2	3.9	5	942	2.9	37.9	7.4
Bug	2009	2	3.8	12.6	879	1.4	55.8	15.6
Reed	2007	1	1.1	17.2	380.4	3.6	17.4	4.9
Reed	2008	1	1.4	7	397.3	1.2	17.2	4.3
Reed	2009	2	2.7	73.3	546	19.8	39.8	7.8
Split 1			**1.2**	**5.7**	**399.7**	**1.7**	**17.3**	**3.9**
Split 2			**3.3**	**13.1**	**648.6**	**2.2**	**38.9**	**7.6**
Squires	2007	1	0.6	4.4	389.1	1.8	10.1	3.6
Squires	2009	1	0.8	3.5	402	3	16.8	2.3
Squires	2008	2	4.4	13.5	751.2	1.4	42.6	13.8
Toad	2007	1	1.5	0.1	406.2	0.8	28.3	5.3
Toad	2008	2	1.7	30.2	505	55.9	9.2	3.5
Toad	2009	2	1.5	6.6	396	1	18.9	5.2

Table 13. Results for Kmeans clustering and categorical groups with association analysis.

	Cluster groups	
Category	**Kmeans 1**	**Kmeans 2**
Cyanobacteria	14	5
Other algae	62	11

Misclassification= 67/92 (73%)
Association analysis not significant: chi-squared = 0.66, df=1, p-value= 0.42

	Cluster groups	
Category	**Kmeans 1**	**Kmeans 2**
High Chlorophyll	19	14
Low Chlorophyll	57	2

Misclassification= 21/92 (23%)
Association analysis significant: chi-squared = 20.999, df=1, p-value$\leq$ 0.0001***

	Cluster groups	
Category	**Kmeans 1**	**Kmeans 2**
High Phosphorus	30	16
Low Phosphorus	46	0

Misclassification= 30/92 (33%)
Association analysis significant: chi-squared = 17.023, df=1, p-value$\leq$ 0.0001***

Table 14. Results for three non-metric clustering runs showing association analysis results.

	Cluster groups	
Category	**NMC 1**	**NMC 2**
Cyanobacteria	13	6
Other algae	33	40

Misclassification= 39/92 (42%)
Association analysis not significant: chi-squared = 2.3879, df=1, p-value= 0.12

	Cluster groups	
Category	**NMC 1**	**NMC 2**
High Chlorophyll	29	3
Low Chlorophyll	17	43

Misclassification= 20/92 (21%)
Association analysis significant: chi-squared = 29.9479, df=1, p-value$\leq$ 0.0001***

	Cluster groups	
Category	**NMC 1**	**NMC 2**
High Phosphorus	36	10
Low Phosphorus	10	36

Misclassification= 20/92 (21%)
Association analysis significant: chi-squared = 27.1739, df=1, p-value$\leq$ 0.0001***

Literature Cited

Anderson, T. 1997. Pelagic Nutrient Cycles, Herbivores as sources and Sinks. Springer Verlag, New York, USA.

Anderson, D.M., Gilbert, P.M., and Burkholder, J.M. 2002. Harmful algal blooms and eutrophication: nutrient sources, composition, and consequences. *Estuaries*, 25, 4b: 704-726.

Brakke, D.F., and Loranger, T.J. 1986. Acid neutralizing capacity of lakes in the North Cascades area of Washington State. *Water, Air, and Soil Pollution*, 39: 1045-1053.

Bortleson, G.C., Dion, N.P., McConnell, J.B., and Nelson, L.M. 1976. Reconnaissance data on lakes in Washington. *Washington Department of Ecology Water Supply Bulletin* 43 (1), Olympia, Washington.

Carey, C.C., Weathers, K.C., and Cottingham, K.L. 2008. *Gloeotrichia echinulata* bloom in an oligotrophic lake: helpful insights from eutrophic lakes. *Journal of Plankton Research*, 30(8): 893-904.

Carpenter, S. R., Caraco, N.F., Correll, D.L., Howarth, R.W., Sharley, A.N. and Smith, V.H. 1998. Nonpoint pollution of surface waters with phosphorus and nitrogen. *Ecological Applications*, 8(3):559-568.

Cole, J.J. Ecology: production in pristine lakes. *Nature*, 460: 463-464.

Crawley, M.J. 2007. The R Book. John Wiley and Sons, Ltd, England.

Davis, T.W., Berry, D.L., Boyer, G.L., and Gobler, C.J. 2009. The effects of temperature and nutrients on the growth and dynamics of toxic and non-toxic strains of *Microsystis* during cyanobacteria blooms. *Harmful Algae*, 8 (5): 715-725.

Dillon, P.J., and Rigler, F.H. 1974. The phosphorus-chlorophyll relationship in lakes. *Limnology and Oceanography*, 19 (5): 767-773.

Dodds, W.K, Bouska,W.W., Eitzmann, J.L., Pilger, T.J., Pitts, K.L., Riley, A.J., Schloesser, J.T., and Thornbrugh, D.J. 2009. Eutrophication of U.S. freshwaters: analysis of potential economic damages. *Environmental Science and Technology,* 43(1): 12-19.

Downing, J.A., Watson, S.B., and McCauley, E. 2001. Predicting cyanobacteria dominance in lakes. *Canada Journal of Aquatic Science*, 58: 1905-1908.

Dokulil, M.T., and Teubner, K. 2000. Cyanobacterial dominance in lakes. *Hydrobiologia,* 438: 1-12.

Everitt, B.S. 1993. Cluster Analysis, Third Edition. John Wiley and Sons Inc. New York, USA.

Gilbert, P.M., Harrison, J., Heil, C., and Seitzinger, S. 2006. Escalating wordwide use of urea- a global change contributing to coastal eutrophication. *Biogeochemistry*, 77:441-463.

Goodman, L.A., and Kruskal, W.H. 1954. Measures of association for cross classifications. *Journal of the American Statistical Association,* 49: 732-764.

Guven, B., and Howard, A. 2006. A review and classification of the existing models of cyanobacteria. *Progress in Physical Geography*, 30 (1): 1-24.

Hamilton, P.B., Proulx, M., and Earle, C. 2001. Enumerating phytoplankton with an upright compound microscope using a modified settling chamber. *Hydrobiologia*, 444: 171-175.

Havens, K. E., James, R.T., East, T.L., Smith, V.H. 2003. N:P ratios, light limitations, and cyanobacterial dominance in a subtropical lake impacted by non-point source nutrient pollution. *Environmental Pollution* 122: 379-390

Havens, K. E. 2008. Cyanobacteria blooms: effects on aquatic ecosystems. In H. H. Kenneth, editor, Cyanobacterial Harmful Algal Blooms: State of the Science and Research Needs. Springer-Verlag, New York, USA.

Howard, A. 2001. Modeling movement patterns of the cyanobacterium, *Microcystis*. *Ecological Applications*, 11(1): 304-310.

Karlsson, J., Bystrom, P., Ask, J., Persson, L., and Jansson, M. 2009. Light limitation of nutrient-poor lake ecosystems. *Nature,* 469: 506-509.

Kaufman, L., and Rousseeuw, P.J. 1990. Finding Groups in Data: An Introduction to Cluster Analysis. Wiley, New York, USA.

MacQueen, J. 1967. Some methods for classification and analysis of multivariate observations. *In Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability*, 1: 281-297.

Maier, H.R., Dandy, G.C., and Burch, M.C. 1998. Use of artificial neural networks for modeling cyanobacteria *Anabaena* spp. In the River Murray, South Australia. *Ecological Modeling* 105: 257-272.

Maier, H.R., Sayed, T., and Lence, B.J. 2001. Forecasting cyanobacterium *Anabaena* spp. In the River Murray, South Australia, using B-spline neurofuzzy models. *Ecological Modeling* 146: 85-96.

Matthews, G., and Hearne, J. 1991. Clustering without a metric. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 13 (2): 175-184.

Matthews, G.B., Matthews, R.A., and Landis, W.G. 1995. Nonmetric clustering and association analysis: implications for the evaluation of multispecies toxicity tests and field monitoring. Environmental Toxicology and Risk Assessment. In Hughes,J.S., Biddinger, G.R., and Mones, E. American Society for Testing and Materials, (3) ASTM 1218,

National American Lake Management Society (NALMS). http://www.nalms .org/nalmsnew/Default.aspx. Accessed 2 May 2010.

North Cascades Audubon Society (NCAS). http://www.northcascadesaudubon. org/index.php. Accessed May 2010.

Onderka, M. 2007. Correlations between several environmental factors affecting the bloom events of cyanobacteria in Liptovska Mara reservoir (Slovakia)- a simple regression model. *Ecological Modeling,* 209 (2-4): 412-416.

Paerl, P.W. 1988. Phytoplankton blooms in costal, estuarine, and inland waters. *Limnology and Oceanography,* 33(4): 823-847.

Paerl, HW. 2008. Chapter 10: Nutrient and other environmental controls of harmful cyanobacterial blooms along the freshwater-marine continuum. In H. H. Kenneth, editor. Cyanobacterial Harmful Algal Blooms: State of the Science and Research Needs. Springer, New York 619: 217-237.

Paul, V.J. 2008. Chapter 11: Global warming and cyanobacterial harmful algal blooms. In H. H. Kenneth, editor. Cyanobacterial Harmful Algal Blooms: State of the Science and Research Needs. Springer-Verlag, New York, USA.

Pettersson, K., Herlitz, E., and Istvanovics, V. 1993. The role of *Gloeotrichis echinulata* in the transfer of phosphorus from sediments to water in Lake Erken. *Hydrobiologia* 253: 123-129.

Prepas, E.E., Planas, D., Gibson, J.J., Vitt, D.H., Prowse, T.D., Dinsmore, W.P., Halsey, L.A., McEachern, P.M., Paquet, S., Scrimgeour, G.J., Tonn, W.M., Paszkowski, C.A., and Wolfstein, K. 2001. Landscape variables influencing nutrients and phytoplankton communities in Boreal Plain lakes of northern Alberta: a comparison of wetland- and upland-dominated catchments. *Canada Journal of Fish and Aquatic Science*, 58: 1286-1299.

R: The R project -http://www.r-project.org/. Accessed October 2009.

Reynolds, C.S., Oliver, R.L., and Walsby, A.E. 1987. Cyanobacteria dominance: the role of buoyancy regulations in dynamic lake environments. *New Zealand Journal of Marine and Freshwater Research*, 21: 379-390.

Reynolds, C.S. 1998. What factors influence the species composition of phytoplankton in lakes of different trophic status? *Hydrobiologia* 369(370): 11-26.

Reynolds, C.S., Huszar, V., Kruk, C., Naselli-Flores, L., and Melo, S. 2002. Towards a functional classification of freshwater phytoplankton. *Journal of Plankton Research*, 24 (5): 417-428.

Rhee, G.Y., and Gotham, I.J. 1980 Optimum N:P ratios and coexistence of planktonic algae. *Journal of Phycology*, 16: 486-489.

Ritchie, R.J., Trautman, D.A., and Larkum, A.W.D. 2001. Phosphate limited cultures of the cyanobacterium synechococcus are capable of very rapid, opportunistic uptake of Phosphate. *New Phytologist,* 152(2): 189-201.

Rodriguez-Perez, H., Lopez-Rodas, V., and Costas, E. 2010. Chapter 9: Phytoplankton (Toxic Algae) as Biological Indicators. In Hurford, C. et al., Conservation Monitoring in Freshwater Habitats: A Practical Guide and Case Studies, Springer Science, New York, USA.

Sakamoto, M. 1966. Primary productivity by the phytoplankton community in some Japanese Lakes and its dependence on lake depth. *Archiv fur, Hydrobiologie*, 62: 1-28.

Sivonen, K. 1996. Cyanobacterial toxins and toxin production. *Phycologia*, 35: 12-24.

Shapiro 1990. Current beliefs regarding dominance by blue-greens the case for the importance of CO2 and pH. *Verhandlungen der Internationale Vereiningung fűr Theoretische und Angerwandte Limnologie*, 24: 38-54.

Smith, V.H. 1982. The Nitrogen Phosphorus dependence of algal biomass in lakes: an empirical and theoretical analysis. *Limnology and Oceanography,* 27(6): 1101-1112.

Smith, V.H. 2003. Eutrophication of freshwater and coastal marine ecosystems-a global problem. *Environmental Science and Pollution Research*, 10(2): 126-139.

Smith, V.H., Joye, S.B., and Howarth, R.W. 2006. Eutrophication of freshwater and marine ecosystems. *Limnology and Oceanography,* 5(1): 351-355.

Smith, V.H., and Schindler, D.W. 2009. Eutrophication science, where do we go from here? *Trends in Ecology and Evolution*, 24(4): 201-207.

Snohomish County, Washington, State of the Lakes Report. 2008. http://www1.co.snohomish.wa.us/Departments/Public_Works/Divisions/SWM/Library/Publications/Water_Quality/StateoftheLakes2006Update.htm. Accessed February 2010.

Stanley, C.D., Clarke, R.A., McNeal, B.L. and MacLeod, B.W. 2003. Relationship of chlorophyll a concentration to seasonal water quality in Lake Manatee, Florida. *The Soil and Water Science Department, Florida Cooperative Extension, IFAS, University of Florida*, http://edis.ifas.ufl.edu. Accessed February 2010.

Tracy, K.L. 2001. Changes in Mirror Lake as a result of the diversion of water from the Nooksack River. AGU fall meeting abstracts. http://adsabs.harvard.edu/abs/2001AGUFM.H41D0310T. Accessed 21 January 2010.

United States Environmental Protection Agency, 1996. Environmental indicators of water quality in the United States, US EPA 841-R-96-02, Office of Water (4503F), US Government Printing Office, Washington DC, USA.

United States Environmental Protection Agency. 2008. US EPA Papers, Cyanobacterial Harmful Algal Blooms: Chapter 9: Causes, Prevention, and Mitigation Workgroup Report. University of Nebraska, Lincoln. http://www.epa.gov/cyano_habs_symposium/monograph.html. Accessed 7 April 2010.

Venables, W.N., and Ripley, B.D. 2002. Modern Applied Statistics with S., Fourth Edition. Springer-Verlag, New York, USA.

Washington Native Plant Society. http://www.wnps.org/. Accessed February 2010.

Washington State Department of Ecology. Freshwater Algae Control Program. http://www.ecy.wa.gov/programs/wq/plants/algae/index.html. Accessed 30 January 2010.

Washington Department of Ecology, Water Quality Assessment for Washington (WQA). 2008. http://apps.ecy.wa.gov/wats08/Default.aspx. Accessed January 2010.

Washington State legislature, 173-201A-230. 2006. http://apps.leg.wa.gov/WAC/default.aspx?cite=173-201A-230. Accessed February 2010.

Washington State Lake Protection Association (WALPA). http://www.walpa.org/. Accessed January 2010.

Washington State House Bill 2322, (Certification of enrollment engrossed HOUSE BILL 2322, chapter 223, laws of 2006, 59th Legislature, 2006 regular session, dishwashing detergent), http://www.walpa.org/documents/Legislation/2322.SL.pdf. Accessed January 2010.

Wetzel, R.G., 2001. Limnology, Lakes and River Ecosystems, Third Edition. Elsevier, Academic Press, 00-110178.

Wolcott, E.E. 1973. Lakes of Washington: Volume 1, Western Washington (Third Edition). Washington State Department of Ecology Water Supply Bulletin 14(1).

Woodard, M.E. 2006. Aquatic macrophyte distribution correspondence to water chemistry in 21 Puget lowland lakes. M.S. Thesis, Western Washington University, Bellingham WA.

World Health Organization. 2003. Algae and cyanobacteria in coastal and estuarine waters: guidelines for safe recreational water environments– *Vol. 1 Coastal and Fresh Waters.* Geneva, Switzerland: World Health Organization, 128(35).

Wynne, T.T, Stumpf, R.P, Tomlinson, M.C. and Dyble, J. 2010. Characterizing a cyanobacterial bloom in western Lake Erie using satellite imagery and meteorological data. *Limnology and Oceanogr*aphy, 55(5): 2025-2036.

Zar, J.H. 1999. Biostatistical Analysis, Fourth Edition. Prentice Hall Publishing. New Jersey, USA.

Appendix 1.

Water Chemistry Parameters Measured for the Small Lakes Monitoring Project

Temperature

All organisms require specific temperature ranges for their survival; any variation to extreme on either end of that range can result in the loss of those organisms. Temperature also plays a key role in the amount of oxygen and nutrients available to the lake ecosystem. Seasonal temperature variation is common and predictable in local lakes: summers are warm and winters are cool. The temperature patterns in our region results in lake stratification during the summer, which is the physical separation of the water column into the epilimnion (surface layer) and the hypolimnion (lower layer), with a region of transition (metalinmion). As the lake cools in the fall, this stratification is lost and the water column mixes in a process called "turnover." Turnover is dependent on microclimate and macroclimate patterns; in general, northwest lakes turnover in the fall (personal communication with Dr. Matthews, Western Washington University, October, 2009).

Dissolved Oxygen

Dissolved oxygen is the amount of oxygen present in water, and can be expressed as a concentration (mg/L), and percent saturation, which is the amount of dissolved oxygen compared to the maximum amount that could be present at the same temperature. In oligotrophic lakes, the amount of oxygen dissolved in the water column is usually close to fully saturated, but in eutrophic lakes the epilimnion may be supersaturated due to photosynthesis and the hypolimnion may have little or no oxygen due to bacterial respiration (Wetzel 2001). The Institute for Watershed Studies measured dissolved oxygen using a field

meter, and reported both concentration and percent saturation. Because these two values are closely associated, I used only concentration (mg/L) for my thesis research.

Alkalinity

Alkalinity is a measure of the buffering capability of the water, which is an indication of how resistant a lake is to a change in pH. Alkalinity is measured by titrating acid into the water and measuring amount of acid required to change to a specific pH level. A buffered (hard-water) lake resists pH change due to the presence of calcium carbonate ($CaCO_3$) or similar compounds (Wetzel 2001). Most of the lakes in our region are poorly buffered (soft-water lakes), so they have low alkalinities (personal communication with Dr. Robin Matthews, Western Washington University, October 2009).

Specific Conductivity

Specific conductivity is a measure of resistance to electrical flow. Pure water lacks the dissolved ions needed to transport electricity, which results in resistance. The presence of dissolved ionic compounds increases the flow of electrons and results in higher conductivity. Temperature also plays a role, increasing conductivity, so conductivity meters are usually temperature compensated and the measurements are reported as µS/cm at 25º C. The concentration of dissolved ions is dependent on the size of the watershed and the geology of the lake basin (Wetzel 2001). For example, a lake basin formed of limestone will have higher conductivity due to dissolved carbonate ions (CO_3^-). The presence of anthropogenic pollutants, such as sewage, agricultural runoff, urban runoff and atmospheric pollution, can also contribute to the conductivity of water (Wetzel 2001, Havens 2008).

pH

The pH in water is a measurement of the concentration of hydrogen ions on a log-scale of 0-14, with 7.0 being neutral. The pH in biologically unproductive lakes is usually slightly acidic due to the presence of carbonic acid (H_2CO_3). In a productive lake, photosynthesis uses carbon dioxide, which temporarily increases the pH of the water during the day. A lake that has a eutrophic epilimnion will often have a pH around 7.5-8.5, or higher, while the pH in comparison to the epilimnion in an oligotrophic lake, which may have a pH of 6.5-7.0 or lower (Wetzel 2001).

Nutrients: Nitrogen and Phosphorus

Nutrients in lakes are essential to the overall productivity of the lake ecosystem, but in large amounts these same nutrients can result in massive algal blooms. Nitrogen and phosphorus are the essential building blocks for most organisms. Heterotrophic organisms absorb these nutrients from consuming photosynthetic plants, algae or higher organisms. Algae, however, usually extract nitrogen and phosphorus from the water. Nutrient availability plays a key role in the development of nuisance algal blooms, but it is still not clear whether nutrients are the determining factor in a cyanobacteria bloom (Reynolds 1998, Paerl 1988).

Nitrogen can be present in the water column as dissolved nitrogen gas (N_2), ammonium (NH_4), nitrate (NO_3), nitrite (NO_2), and organic nitrogen. Phosphorus is usually attached to small particles or in living biomass, but a small amount may be dissolved in water. Dissolved phosphorus (soluble reactive phosphorus or orthophosphate) is easily taken up by microorganisms. Most algae can only use nitrogen in the form of ammonium, nitrite,

or nitrate. Cyanobacteria, however, are able to fix dissolved N_2, which gives them access to a nearly unlimited form of nitrogen (Wetzel 2001).

Chlorophyll α

Chlorophyll α is a photosynthetic pigment found in all algae, making it a good measure of photosynthetic biomass. The amount of chlorophyll α in the water column changes seasonally as algal populations rise (spring) and decrease (autumn). Winter tends to have the lowest chlorophyll levels as there is less sunlight and cooler temperatures. For the small lakes project, chlorophyll samples were collected approximately 2-3 meters off-shore using a sampling pole to minimize contamination from sediments along the shoreline. The Institute for Watershed Studies uses a phaeophytin correction method to subtract degraded chlorophyll (phaeophytin) so their results represent the undegraded chlorophyll α concentration. For simplicity, I will refer to chlorophyll α as "chlorophyll" in my thesis.

Turbidity

Turbidity is a measure of water clarity that is affected by amount of suspended particulates in the water column. There are three major types of suspended particles: silt, detritus and phytoplankton. Silt (inorganic, minerals or sediments) comes from soil erosion or lake mixing, which suspends bottom sediments. Detritus (dead algae, plants, and zooplankton as well as fungi and bacteria) can be washed in from upstream or produced within the lake. Phytoplankton concentrations fluctuate seasonally and are largely dependent on nutrient and light availability. In the small lakes project, turbidity was measured using a nephelometer and reported in nephelometric turbidity units (NTU). High turbidities are generally

associated with eutrophic lakes or lakes that receive large inputs of suspended particulates (e.g., glacial lakes, Wetzel 2001).

Appendix 2.

Detailed Lake Descriptions and GIS Maps

Armstrong Lake, Snohomish Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.2258	-122.12291	24 ft	30 acres	174 ft
		(7.3 m)	(12.1 ha)	(53 m)

Armstrong Lake is located 2.5 miles (4 km) north of the town of Arlington, Washington. The watershed area is estimated to be 369 acres and is largely undeveloped. There is public access on the south end of the lake, and gasoline-powered motors are prohibited. Washington Department of Fish and Wildlife stocks the lake with rainbow trout every spring. A report in 2008 assessed the health of the lake, concluding that more consistent data needed to be collected in order to determine its overall health (Snohomish County, 2008).

Bagley Lake (Lower) and Bagley Lake (Upper), Whatcom County

	Latitude	Longitude	Max Depth	Surface Area	Elevation
Bagley (U)	48.8596	-121.68474	N/A	9 acres (3.6 ha)	4334 ft (1321 m)
Bagley (L)	48.8542	-122.69177	N/A	11 acres (4.5 ha)	4334 ft (1321 m)

The Bagley lakes are located on Mt. Baker, Washington. The geology of this area is different from the lower elevation lakes. They lie in a basin created by a quaternary volcano 2 million years ago (Brakke and Loranger 1986). Both lakes are part of the Mount Baker Wilderness Area. Access to these lakes is by foot, and only flat-bottomed boats are allowed. The Institute for Watershed Studies began sampling these lakes in 2006.

Beaver Lake, Skagit Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.4467	-122.22084	unknown	unknown	30 ft (9.1 m)

Beaver Lake is located 1 mile (1.6 km) southeast from the town of Clear Lake, Washington. Beaver Lake is part of the Skagit River basin and flows to the southwest, merging with the East Fork of Nookahamps Creek and the Skagit River (Wolcott 1973). Beaver Lake can be classified as a shallow, productive lake with a mucky littoral bottom (Woodard 2007). This lake is designated primarily for recreation and public access fishing. In 2009, Washington Department of Fish and Wildlife stocked Beaver Lake with triploid rainbow trout (sterile). According to the Department of Ecology, Beaver Lake was listed under 303(d) Impaired Water ways due to the presence of Eurasian mil-foil *(Myriophyllum spicatum)*, an invasive plant (Washington Department of Ecology, 2008).

Big Lake, Skagit Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.38485	-122.23322	23 ft (7.0 m)	520 acres (210.4 ha)	82 ft (25.0 m)

Big Lake is located 5 miles (8 km) southeast of Mount Vernon, Washington. Big Lake is open year round for fishing and has a Washington Department of Fish and Wildlife boat launch. The Washington State Department of Ecology has listed Big Lake on the 303(d) list due to invasive plants and phosphorus loading (Washington Department of Ecology, 2008).

Bug Lake, Whatcom County

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.7765	-122.47315	unknown	unknown	107 ft (32.6 m)

Bug Lake is located off Squalicum Way in Bellingham, Washington. Bug Lake is a retention pond, similar to Sunset Pond. It is located in a developed area of Bellingham. There is no boat access to Bug Lake.

Cain Lake, Whatcom County

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.6470	-122.32909	62 ft (18.9 m)	72 acres (29.1 ha)	391 ft (119.2 m)

Cain Lake is located 9.5 miles (15.3 km) south of Bellingham, Washington. Cain Lake is part of the Samish River basin. Reed Lake flows into Cain Lake from the north. Cain Lake drains to the south into Samish River via Silver Creek (Wolcott 1973). The lake has private residences around the shoreline. The lake has public access and is stocked with fish by Washington Department of Fish and Wildlife.

Lake Campbell, Skagit Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.4404	-122.62045	15 ft (4.6 m)	410 acres (165.9 ha)	43 ft (13.1 m)

Lake Campbell is located on Fidalgo Island, 5 miles (8 m) south of Anacortes, Washington. There are private residences around the lake as well as public access points. Lake Campbell is popular for recreational boating, personal watercraft and year-round fishing. The lake drains to Skagit Bay from an outlet on the southeast shore (Wolcott 1973), and has tributaries that come from Erie, Whistle and Trafton Lakes. The Washington Department of Ecology listed Lake Campbell on the 303(d) list due to an invasive plant Eurasian mil-foil and phosphorus loading (Washington Department of Ecology, 2008).

Canyon Lake, Whatcom County

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.8326	-122.06995	unknown	unknown	2316 ft (706.0 m)

Canyon Lake is located east on Mt. Baker Hwy (542), Washington. The lake is part of a 2300 acre forest that was conserved by Paul G. Allen Forest Protection Foundation, the Whatcom County Conservation Futures Fund, Whatcom Land Trust, Western Washington University and Whatcom County Parks & Recreation. The Canyon Lake trail is a popular hike, and meanders through a mix of second growth and old growth forest. From the viewpoints you can see the historic landslide that most likely formed the lake, as a result of a major earthquake within the last 200 years.

Cavanaugh Lake, Skagit Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.3182	-122.00169.	80 ft (24.4 m)	884 acres (357.7 ha)	1016 ft (309.8 m)

Cavanaugh Lake is located 3 miles (4.8 km) south of Sedro Woolley, Washington. This lake is popular for sport fishing and boating. Cavanaugh Lake is surrounded by private residences and it has a Washington Department of Fish and Wildlife public boat launch,

Cedar and Pine Lakes, Whatcom County

	Latitude	Longitude	Max Depth	Surface Area	Elevation
Pine Lake	48.6754	-122.44403	unknown	unknown	1617 ft (492.7m)
Cedar Lake	48.67777	-122.44936	unknown	unknown	1542 ft (470.0 m)

Cedar and Pine Lakes are located off old Samish Road, Whatcom County, Washington. The hike to Pine Lake is 2.1 miles and Cedar Lake it is 2 miles. There is a hiking trail that surrounds both lakes and the area is scenic and heavily forested. There has been logging in the past but this area is part of the Chuckanut Mountain Trail System. These lakes are a popular hiking and fishing destination and are stocked with cutthroat by the Washington Department of Fish and Wildlife.

Clear Lake, Skagit Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.4614	-122.22576	44 ft	200 acres	30 ft
		(13.4 m)	(80.9 ha)	(9.1 m)

Clear Lake is located 3 miles (4.8 km) south of Sedro Woolly, Washington. There have been two invasive plant species recorded at Clear Lake: Eurasian water-milfoil and fragrant waterlily (*Nymphaea odorata,* Washington Department of Ecology, 2008). Clear Lake is stocked with non-native fish and has a Washington Department of Fish and Wildlife public boat launch.

Crabapple Lake, Snohomish Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.1315	-122.27302	49 ft	38 acres	436 ft
		(14.9 m)	(15.4 ha)	(132.9 m)

Crabapple Lake is located north of the Seven Lakes area, just north of the Tulalip Reservation and east of Lake Goodwin, Washington. The watershed area is roughly 690 acres and includes the Seven Lakes area. The shoreline has been developed, and many residences surround the lake. Lake Loma feeds into Crabapple Lake. Snohomish County did a lake assessment in 2003 for Crabapple Lake and classified it as a mesotrophic lake that does occasionally have cyanobacteria blooms (Snohomish County, 2008).

Cranberry Lake, Island County

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.3953	-122.65655	25 ft	125 acres	275 ft
		(7.6 m)	(50.6 ha)	(83.2 m)

Cranberry Lake is located in Deception Pass State Park, on the north end of Whidbey Island, Washington. Its inflow is intermittent and the lake drains to Rosario Strait. The lake is stabilized by a dam at its northern end. According to the Department of Ecology, Cranberry Lake has a large community of macrophytes and is considered eutrophic, often with a summer algal bloom. Motorized boats are prohibited on the lake.

Deer Lake, Island County

Latitude	Longitude	Max Depth	Surface Area	Elevation
47.9748	-122.38214	50 ft	81 acres	300 ft
		(15.2 m)	(32.8 ha)	(91.4 m)

Deer Lake is located 1 mile (1. 6 km) west of Clinton, Washington, on Whidbey Island. Deer Lake is stocked with trout by Department of Fish and Wildlife and has a public access point on its northeastern corner. The Washington State Department of Ecology has listed Deer Lake on its 303(d) Impaired Waterways list, due to phosphorus (Washington Department of Ecology, 2008).

Erie Lake, Skagit Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.4524	-122.63944	12 ft	111 acres	90 ft
		(3.7 m)	(44.9 ha)	(27.4 m)

Erie Lake is located 4 miles south of Anacortes, Washington. The Erie Lake outflow drains into Campbell Lake and the Skagit Bay (Wolcott 1973). The lake is used for fishing, boating and recreation. The Washington State Department of Ecology has listed Erie Lake on the 303(d) list due to invasive plants and phosphorus loading (Washington Department of Ecology, 2008).

Fazon Lake, Whatcom County

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.8655	-122.36901	16 ft	34 acres	128 ft
		(4.9 m)	(13.8 ha)	(39.0 m)

Fazon Lake is located 1.5 miles (2.4 km) northwest of Goshen, Washington. Fazon Lake is developed and is surrounded by farms and private residences. Fishing is the predominant activity and has played a crucial role in the history and management of the lake. There is both private and public access. The lake has been treated at least 3 times (1970, 1976 and 1980) with rotenone, a piscicide. The Washington State Department of Ecology lists Fazon Lake on the 303(d) Impaired Waterways list due to mercury levels (Washington Department of Ecology, 2008).

Lake Goodwin, Snohomish Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.1390	-122.29508	49 ft	525 acres	318 ft
		(14.9 m)	(212.5 ha)	(97.0 m)

Lake Goodwin is located in the Seven Lakes area of Washington, north of the Tulalip Reservation. Lake Goodwin is classified by Snohomish County as its second most developed lake, with approximately 381 homes around its perimeter. Its shoreline has less than 4% of its native vegetation intact (Snohomish County, 2008). Lake Goodwin is classified as an oligo-mesotrophic lake, and has more frequent algae blooms as well as higher chlorophyll levels since the 1970's (Snohomish County, 2008). Lake Goodwin is fed by Loma Lake and Crabapple Lake, and drains into Shoecraft Lake.

Goss Lake, Island County

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.0386	-122.47909	60 ft	47 acres	62 ft
		(18.3 m)	(19.0 ha)	(18.9 m)

Goss Lake is located 3 miles (4.8 km) west of Langley, Washington and 1 mile from Lone Lake, on Whidbey Island. There are three intermittent streams that flow into the lake, but there is no lake outlet. Goss Lake is open to recreation, with public access on its eastern shore. Trout are stocked in the lake and gasoline-powered boats are prohibited. The Department of Ecology has listed Goss Lake on its 303(d) Impaired Waterways list due to an invasive species (Eurasian water milfoil, *Myriophyllum spicatum*). The Department of Ecology has reported the presence of toxic cyanobacteria since sampling efforts began in 2008 (Washington Department of Ecology, 2008).

Grandy Lake, Skagit Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.5659	-121.80090	unknown	unknown	804 ft
				(245.0 m)

Grandy Lake is located off Baker Lake road, northwest of Concrete, Washington. To the east is Lake Shannon and to the south of Grandy Lake is Highway 20. Grandy Lake is a well known fishing spot throughout the State. It is stocked with bass by the Washington Department of Fish and Wildlife.

Heart Lake, Skagit Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.4750	-122.63100	18 ft	61 acres	325 ft
		(5.5 m)	(24.7 ha)	(99.0 m)

Heart Lake is located 2 miles (3.2 km) south of Anacortes, Washington. The lake is part of Heart Lake State Park and is forested on the northshore. There is a Washington Department of Fish and Wildlife public boat launch at the lake, which makes it popular for fishing and recreation. Heart Lake drains into Fidalgo Bay (Wolcott 1973). The Washington State Department of Ecology has listed Heart Lake on the 303(d) list due to invasive plants (Washington Department of Ecology, 2008).

Lake Howard, Snohomish Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.1577	-122.32711	50 ft	27 acres	246 ft
		(15.2 m)	(10.9 ha)	(74.9 m)

Lake Howard is located 7.5 miles (12 km) northwest of Marysville, Washington. Lake Howard is stocked with non-native fish by the Washington Department of Fish and Wildlife. There is public access and motorized engines are prohibited on the lake.

Ketchum Lake, Snohomish Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.2819	-122.34369	unknown	20 acres	226 ft
			(8.1 ha)	(68.9 m)

Ketchum Lake is located 3 miles (4.8) north of the town of Stanwood, Washington. There is public access to the lake, and it is stocked with non-native sport fish by the Washington Department of Fish and Wildlife.

Ki Lake, Snohomish Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.1515	-122.26500	62 ft	96 acres	436 ft
		(18.9 m)	(38.8 ha)	(132.8 m)

Ki Lake is located off Interstate 5, 7 miles (11.2 km) north of the Tulalip Reservation, Washington. The watershed area is approximately 452 acres, and classified as 40% developed according to the state public works (Snohomish County, 2008). There is public access off State Highway 531 (Lakewood Road). Unlike many lakes in this study area, Ki Lake is monitored on a regular basis by Snohomish County.

Loma Lake, Snohomish Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.1342	-122.25284	30 ft	21 acres	564 ft
		(9.1 m)	(8.5 ha)	(171.9 m)

Loma Lake is located in the Seven Lakes area, approximately 6.5 miles (10.5 km) northwest of Marysville, Washington. Loma Lake is stocked with fish by the Washington Department of Fish and Wildlife, and has public access. Gasoline-powered boats are prohibited on Loma Lake. Snohomish County has conducted milfoil eradication and applied herbicides to the lake (Snohomish County, 2008).

Lone Lake, Island County

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.0235	-122.45906	17 ft	101 acres	0 ft
		(5.18 m)	(40.9 ha)	

Lone Lake is located 2.5 miles (4 km) southwest of Langley, Washington and 1 mile southeast of neighboring Goss Lake, on Whidbey Island. Lone Lake is fed by two small inlets and drains into Useless Bay. Lone Lake is stocked with trout throughout the year, and there is a public access provided on its northern shore. The Washington State Department of Ecology has listed Lone Lake on the 303(d) list due to dioxin as well as, 33 priority pollutants listings for other chemicals (Washington Department of Ecology, 2008).

McMurray Lake, Skagit Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.3155	-122.22689	48 ft	160 acres	232 ft
		(14.6 m)	(64.7 ha)	(70.7 m)

McMurray Lake is located 9 miles (14.5 km) northwest of Arlington, Washington. The lake is stocked with fish by the Washington Department of Fish and Wildlife and the fishing season is opened from April to October. There is a resort on one end of the lake, and many private residences around its perimeter. There are 13 stream inflows, and the lake drains via a concrete weir on the north shore to Big Lake, Nookachamps Creek and the Skagit River (Wolcott, 1973). The Washington State Department of Ecology has listed McMurray Lake on the 303(d) Impaired Waterways List due to invasive plants (Washington Department of Ecology, 2008).

Martha Lake (also known as Lake Martha), Snohomish Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.1681	-122.33975	70 ft	62 acres	207 ft
		(21.3 m)	(25.1 ha)	(63.0 m)

Martha Lake is located in the Seven Lakes area, approximately 10 miles (16 km) north of Marysville, Washington. There are two Martha Lakes in Snohomish County (the other is Martha Lake located near Alderwood Manor). Martha Lake is fed by Lake Howard and drains to Port Susan. Martha Lake is stocked with rainbow and cutthroat trout by the Washington Department of Fish and Wildlife. There is a resort on the lake and there are residential houses along its shores.

Lake Louise, Whatcom County

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.70919	-122.32766	unknown	unknown	412 ft
				(125.5 m)

Lake Louise is located in the Lake Louise National Resource Conservation Area, Sudden Valley, Washington. Lake Louise is part of the 138 acre National Resource Conservation Area, through the Department of Natural Resources. The Whatcom County parks service maintains the area. Lake Louise National Resource Conservation Area is a popular birding and fishing destination. Lake Louise is a manmade reservoir and the Washington Department of Fish and Wildlife stock the lake with fish. The lake shore is mostly undeveloped with a few private residences. There is a pubic boat launch.

Mirror Lake, Whatcom County

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.6630	-122.21937	unknown	unknown	350 ft (106.6 m)

Mirror Lake is located southwest of Acme, off Highway 9 and Park Road in Whatcom County, Washington. Mirror Lake has been in use since 1962 by the city of Bellingham, as a settling pond for the water diverted from the Middle Fork Nooksack River (Tracy 2001). There is fishing access to the lake. The Washington State Department of Ecology has listed Mirror Lake on the 303(d) list for Impaired Waterways due to phosphorus (Washington Department of Ecology, 2008).

Lake Padden, Whatcom County

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.7002	-122.44789	59 ft (17.9 m)	160 acres (64.7 ha)	438 ft (133.5 m)

Lake Padden is located just off Samish Way (I-5 exit 252), in Bellingham, Whatcom County, Washington. Lake Padden is a popular recreation area with hiking trails, picnic areas, swimming, fishing and boating (no gasoline engines). The Washington State Department of Ecology listed Lake Padden on the 303(d) list for Impaired Waterways due to PCB (Polychlorinated biphenyls) loads (Washington Department of Ecology, 2008).

Pass Lake, Skagit Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.4191	-122.63761	18 ft (5.5 m)	unknown	130 ft (39.6 m)

Pass Lake is located 6 miles (9.7 km) south of Anacortes, Washington, and just north of Deception Pass. The area surrounding Pass Lake is mostly forested, though a highway runs along its southern shore. The west side of the lake is in Deception Pass State Park, and hence is used recreationally for both fishing and boating. It has no inflow, but have subsurface outflow into Reservation Bay

Picture Lake, Whatcom County

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.8654	-121.67709	unknown	unknown	4176 ft (1272.8 m)

Picture Lake is located off the road at the Mt Baker Ski Area, Washington. The entire shoreline is surrounded by Highway 542 and there is a walking path around the lake.

Reed Lake, Whatcom County

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.6568	-122.33132	unknown	unknown	365 ft (111.3 m)

Reed Lake is located east of Interstate 5 south of Bellingham, Washington. Reed Lake is southwest of Lake Whatcom and drains into Cain Lake. Much of the water from Reed Lake is diverted and the shoreline is very developed. The lake is a popular fishing destination and

only electric motors are allowed. The Washington Department of Fish and Wildlife stock Reed Lake with fish. The Washington Department of Ecology has recorded a high number of invasive plants both within the lake and around its shoreline, but is currently not listed on the 303(d) list (Washington Department of Ecology, 2008).

Shoecraft Lake, Snohomish Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.1306	-122.30319	69 ft	132 acres	331 ft
		(21.9 m)	(53.4 ha)	(100.9 m)

Shoecraft Lake is located in the Seven Lakes area, north of Tulalip Reservation, Washington. The lake watershed is part of the Seven Lakes area and encompasses roughly 763 acres. The lake is stocked with fish by the Washington Department of Fish and Wildlife and is popular area for recreation. Shoecraft Lake is just to the west of Lake Goodwin.

Silver Lake, Whatcom County

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.9778	-122.06970	unknown	180 acres	765 ft
			(72.8 ha)	(233.2 m)

Silver Lake is located off Highway 542, 3 miles (4.8 km) north of the town Maple Falls, Washington. Silver Lake is a county park with camping and recreation. It is a popular fishing, swimming and boating destination. Most of the lake is forested with intermittent cabins and camping. The lake is stocked with fish and warns public about swimmers itch (*cercarial dermatitis),* caused from a trematode parasite from aquatic birds. Silver Lake has seasonal surface water inflow and drains from the south to the North Fork Nooksack River

from Maple Creek (Wolcott 1973). The Washington State Department of Ecology has listed Silver Lake on the 303(d) list for Impaired Waterways due to invasive plants, PCB, TCDD (Tetrachlorodibenzodioxin) and phosphorus (Washington Department of Ecology, 2008). During 2008-2009, Silver Lake had a toxic cyanobacteria bloom (Washington Department of Ecology, 2008).

Sixteen Lake, Skagit Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.3438	-122.28907	25 ft	41 acres	436 ft
		(7.6 m)	(16.6 ha)	(132.9 m)

Sixteen Lake is located 2.5 miles (4 km) east of Conway, Washington. The lake is used for recreation and fishing and is stocked by the Washington State Department of Fish and Wildlife. There are no inflows or outflows from Sixteen Lake (Bortleson et al. 1976). The Washington State Department of Ecology has listed Sixteen Lake on the 303(d) Impaired Waterways List due to an invasive plant species, Eurasian water milfoil (*Myriophyllum spicatum*; Washington Department of Ecology, 2008).

Squalicum Lake, Whatcom County

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.7984	-122.34969	unknown	33 acres	477 ft
			(13.4 ha)	(145.4 m)

Squalicum Lake is located 6.5 miles northeast of Bellingham, Washington. The lake is surrounded by private residences, wetlands and pasture. Squalicum Lake is used recreationally and is popular for fishing.

Squires Lake, Skagit/Whatcom County Border Lake

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.6459	-122.35393	unknown	10 acres (4.0 ha)	420 ft (128.0 m)

Squires Lake is located off Old Highway 99, south of Bellingham, Washington, on the border of Whatcom and Skagit Counties. Squires Lake was privately owned by the Squires family until 1995, when the Whatcom Land Trust made it a conservation area. It has a history of fish and muskrat being stocked for hunting and fishing.

Summer Lake, Skagit Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.3329	-122.16783	unknown	unknown	531 ft (161.9 m)

Summer Lake is located north of Arlington, in the Lake McMurray area, Skagit County Washington. The Washington Native Plant Society did a plant survey in 1990, noting the presence of multiple non-native invasive aquatic plants (Washington Native Plant Society, 2010). Summer Lake is stocked with fish from the Washington Department of Fish and Wildlife.

Sunday Lake, Snohomish Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.2289	-122.25691	20 ft (6.0 m)	38 acres (15.4 ha)	223 ft (68.0 m)

Sunday Lake is located 5 miles (8 km) to the east of Stanwood, Washington. The watershed area is roughly 790 acres and mostly undeveloped. The access is walk-in and gasoline-powered engines are prohibited. The Washington Department of Fish and Wildlife stocks Sunday Lake with rainbow trout. According to Snohomish County, in their 2008 State of the Lakes report, Sunday Lake suffers from high nutrients, algal blooms and poor water clarity. The lake is classified as eutrophic (Snohomish County, 2008).

Sunset Lake (Pond), Whatcom County

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.7763	-122.46124	unknown	unknown	133 ft (40.5 m)

Sunset Pond is located off North James Street in Bellingham, Washington. Sunset Pond is a manmade retention pond, resulting from a construction site. The Washington Department of Fish and Game stock Sunset Pond with fish. The pond is used primarily for fishing and an off-leash dog area. Squalicum Creek runs through the pond.

Tennant Lake, Whatcom County

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.8311	-122.57962	unknown	80 acres (32.4 ha)	0 ft

Tennant Lake is located 1 mile (1.6 km) southeast of Ferndale, Washington. Tennant Lake is part of the 360 acre Whatcom Wildlife Area, designated by Washington Department of Fish and Wildlife. The area is mostly a floodplain of the Nooksack River. The Whatcom Wildlife Area has a visitor center and is popular for birding and hunting.

Lake Terrell, Whatcom County

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.8606	-122.68476	10 ft	500 acre	210 ft
		(3.0 m)	(202.4 ha)	(64.0 m)

Lake Terrell is located 5 miles (8 km) west of the town Ferndale, Washington. It is a 500 acre manmade lake with peat bogs on each end. Lake Terrell is part of the larger Lake Terrell Wildlife Area, designated in 1947. The Lake Terrell Wildlife Area is 1500 acres. Famous for its birding, wild rice has been planted in the lake since 1988 to attract waterfowl. Lake Terrell hosts an array of introduced fish species and is a very popular fishing and hunting destination.

Toad (Emerald) Lake, Whatcom County

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.7906	-122.39653	31 ft	29 acres	806 ft
		(9.5 m)	(11.7 ha)	(245.7 m)

Toad Lake is located 5 miles (8 km) northeast of Bellingham, off of Highway 542, Bellingham, Washington. There are private residences surrounding the lake and limited public access on the southeast end. Toad Lake is popular for boating, fishing and swimming. Motor boats are prohibited on the lake. Toad Lake is stocked with trout and Kokanee by the Washington Department of Fish and Wildlife. The lake drains to Toad Creek, Squalicum Creek and Bellingham Bay.

Twin Lake (Upper) and Twin Lake (Lower), Whatcom County

	Latitude	Longitude	Max Depth	Surface Area	Elevation
Twin Lake (U)	48.9522	-122.63408	unknown	20 acres (8.1 ha)	5184 ft (1580 m)
Twin Lake (L)	48.9507	-121.63925	unknown	20 acres (8.1 ha)	5184 ft (1580 m)

The Twin Lakes are located 14 miles (22.5 km) away from the town of Glacier, Washington. The Twin Lakes area is only accessible in mid August, when the snow melts. The Twin Lakes are a popular hiking and fishing destination. The access to the lakes is by Road #3065 off the Shuksan Highway.

Vogler Lake, Skagit Country

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.5712	-121.7737	10 ft (3.0 m)	3.7 acres (1.5 ha)	1079 ft (328.9 m)

Vogler Lake is located 2.5 (4 km) miles north of Concrete, Washington. The Washington Department of Fish and Wildlife stocks Vogler Lake with rainbow trout. Vogler Lake is very close to Lake Tyee. Motor boats are prohibited and the lake is a popular fly fishing destination.

Wiser Lake, Whatcom County

Latitude	Longitude	Max Depth	Surface Area	Elevation
48.9032	-122.48040	11 ft (3.4 m)	103 acres (41.7 ha)	70 ft (21.3 m)

Wiser Lake is located 3 miles (4. 8 km) southwest of Lynden, Washington. Wiser Lake is divided by Meridian Road. The eastside of the lake is surrounded by houses and the westside is surrounded by agriculture and dairy fields. The lake has a littoral mucky bottom and it drains via Wiser Lake Creek to the Nooksack River (Wolcott 1973). Wiser Lake is open to the public for recreation. The Department of Ecology has been monitoring Wiser Lake since 1997. Over the past decade the lake has had many cyanobacteria blooms. The Washington State Department of Ecology has listed Wiser Lake on the 303(d) Impaired Waterways List due to mercury levels (Washington Department of Ecology, 2008).

Figure 19. GIS map of Armstrong Lake, Snohomish County, WA.

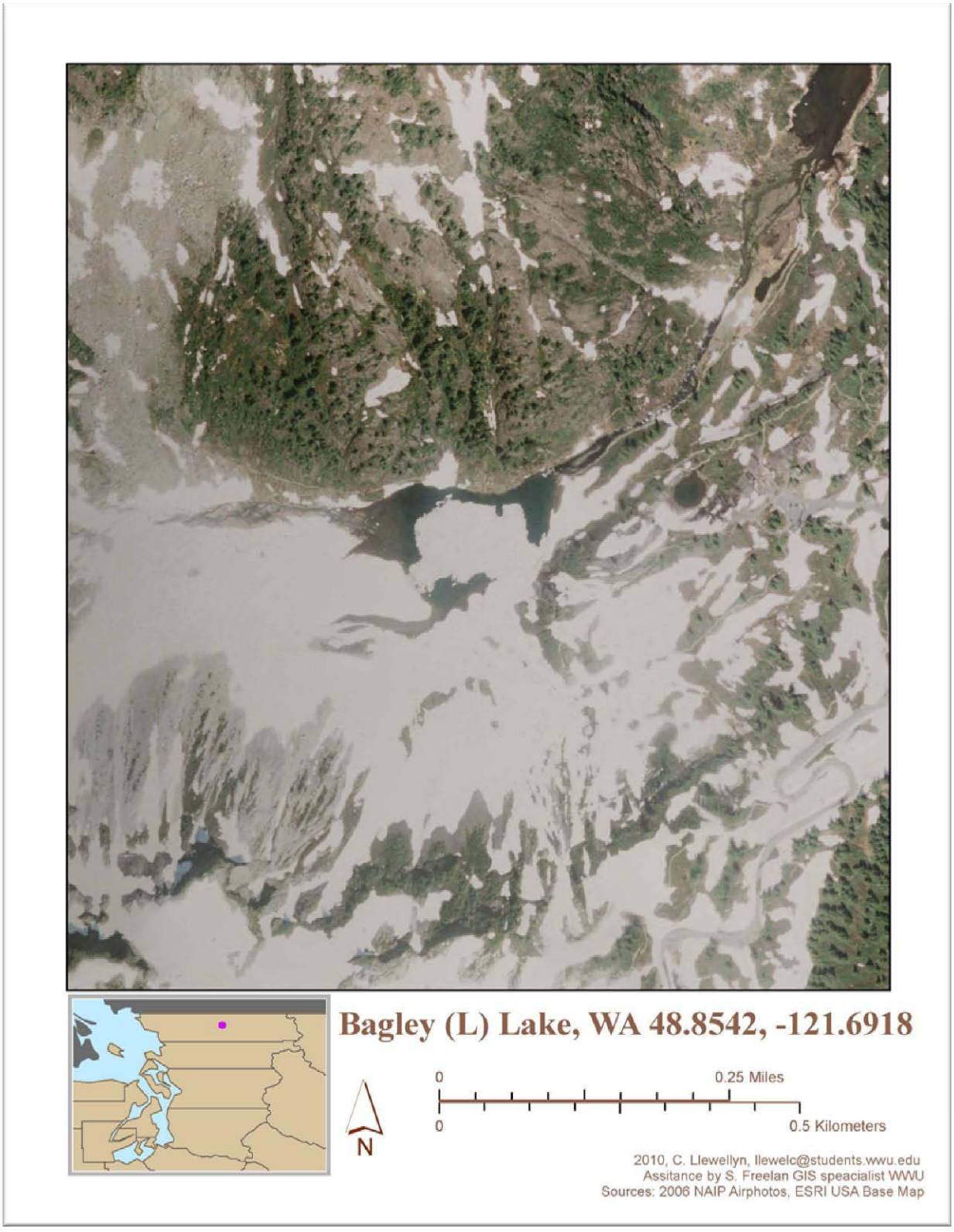


Figure 20. GIS map of Lower Bagley Lake, Whatcom County, WA.

Figure 21. GIS map of Upper Bagley Lake, Whatcom County, WA.

Figure 22. GIS map of Beaver Lake, Skagit County, WA.

Figure 23. GIS map of Big Lake Skagit County, WA.

Figure 24. GIS map of Bug Lake, Whatcom County, WA.

Figure 25. GIS map of Cain Lake, Whatcom County, WA.

Figure 26. GIS map of Lake Campbell, Skagit County, WA.

Figure 27. GIS map of Canyon Lake, Whatcom County, WA

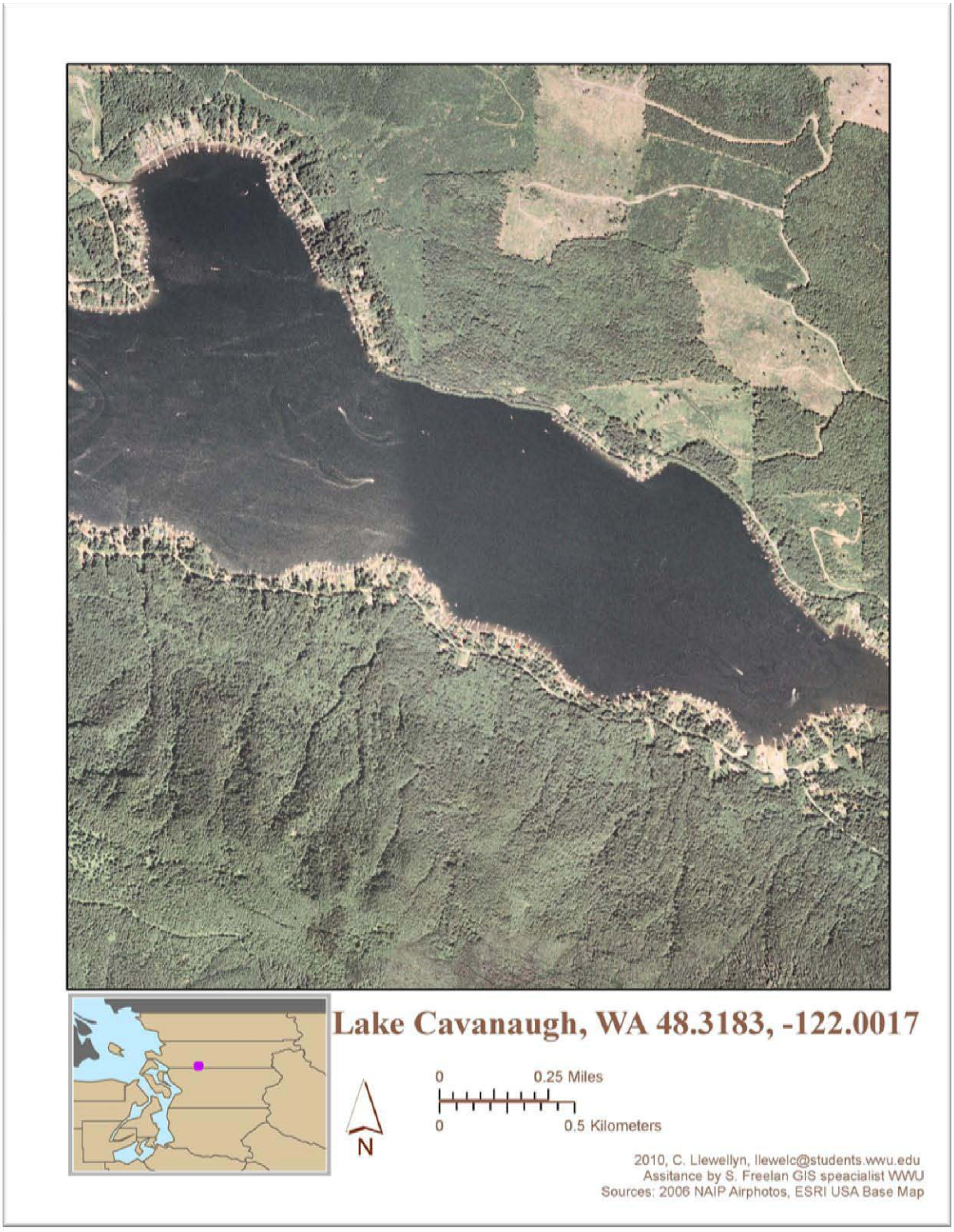


Figure 28. GIS map of Lake Cavanaugh, Skagit County, WA

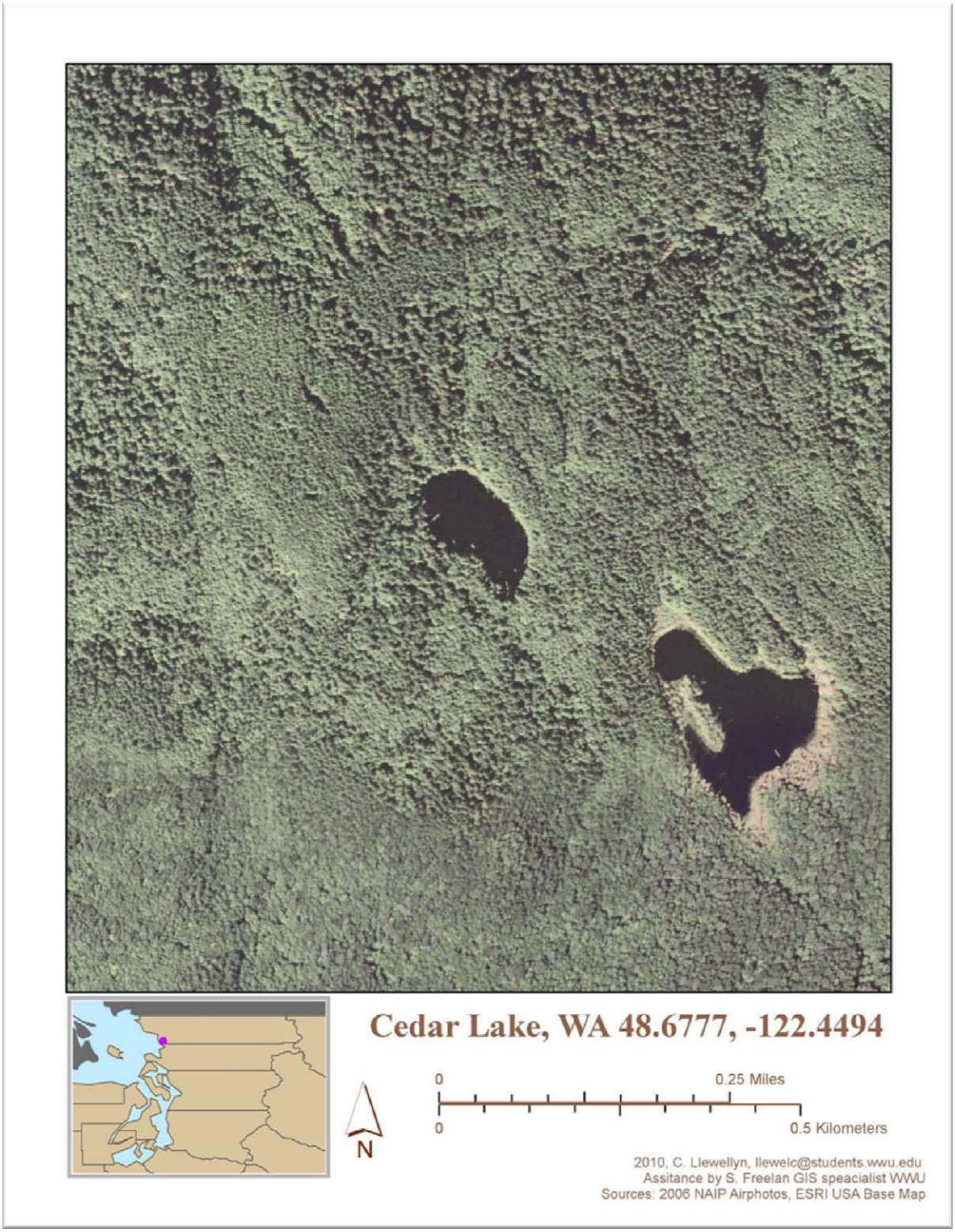


Figure 29. GIS map of Cedar Lake, Whatcom County, WA

Figure 30. GIS map of Clear Lake, Skagit County, WA

Figure 31. GIS map of Crabapple Lake, Snohomish County, WA

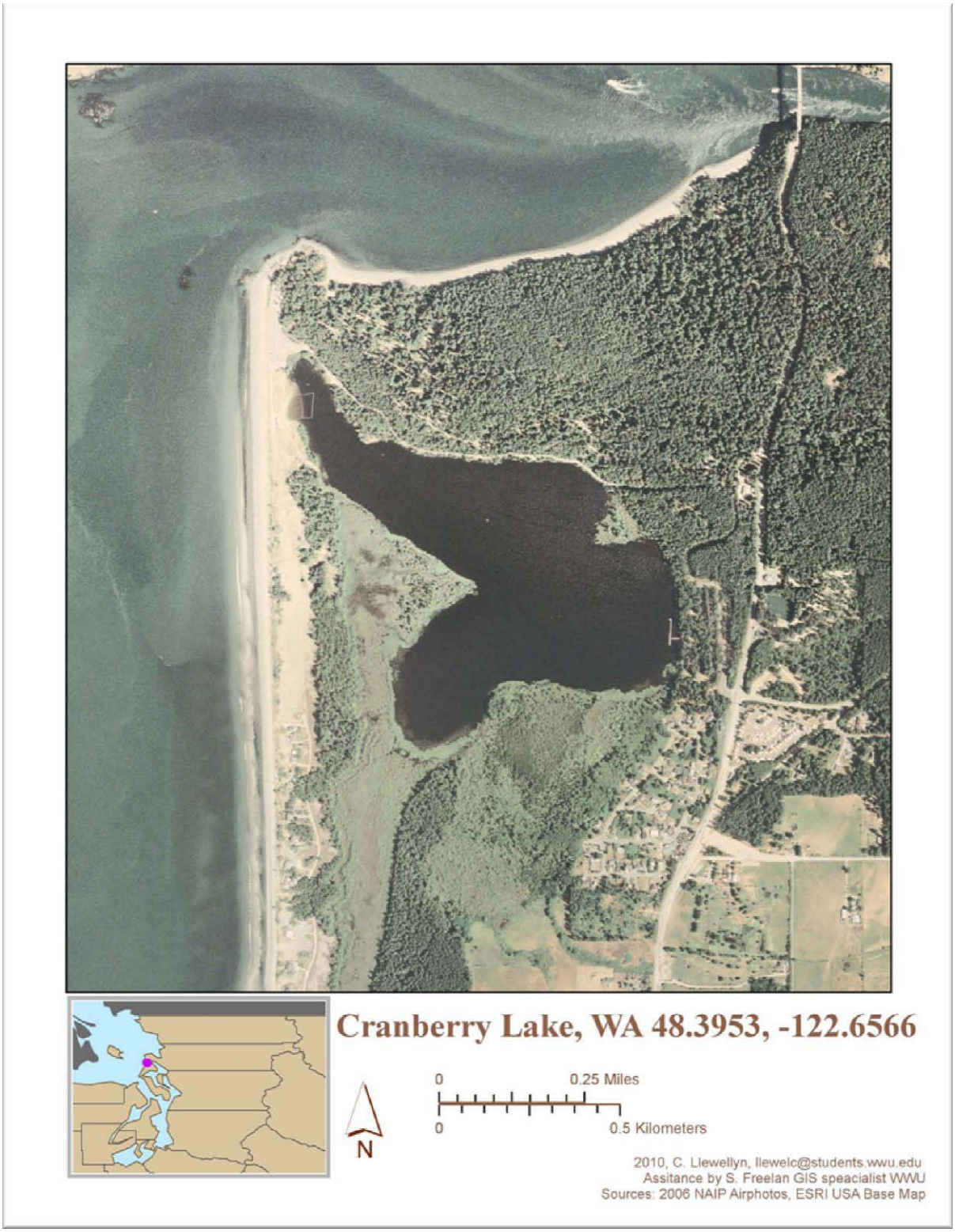


Figure 32. GIS map of Cranberry Lake, Island County, WA

Figure 33. GIS map of Deer Lake, Island County, WA

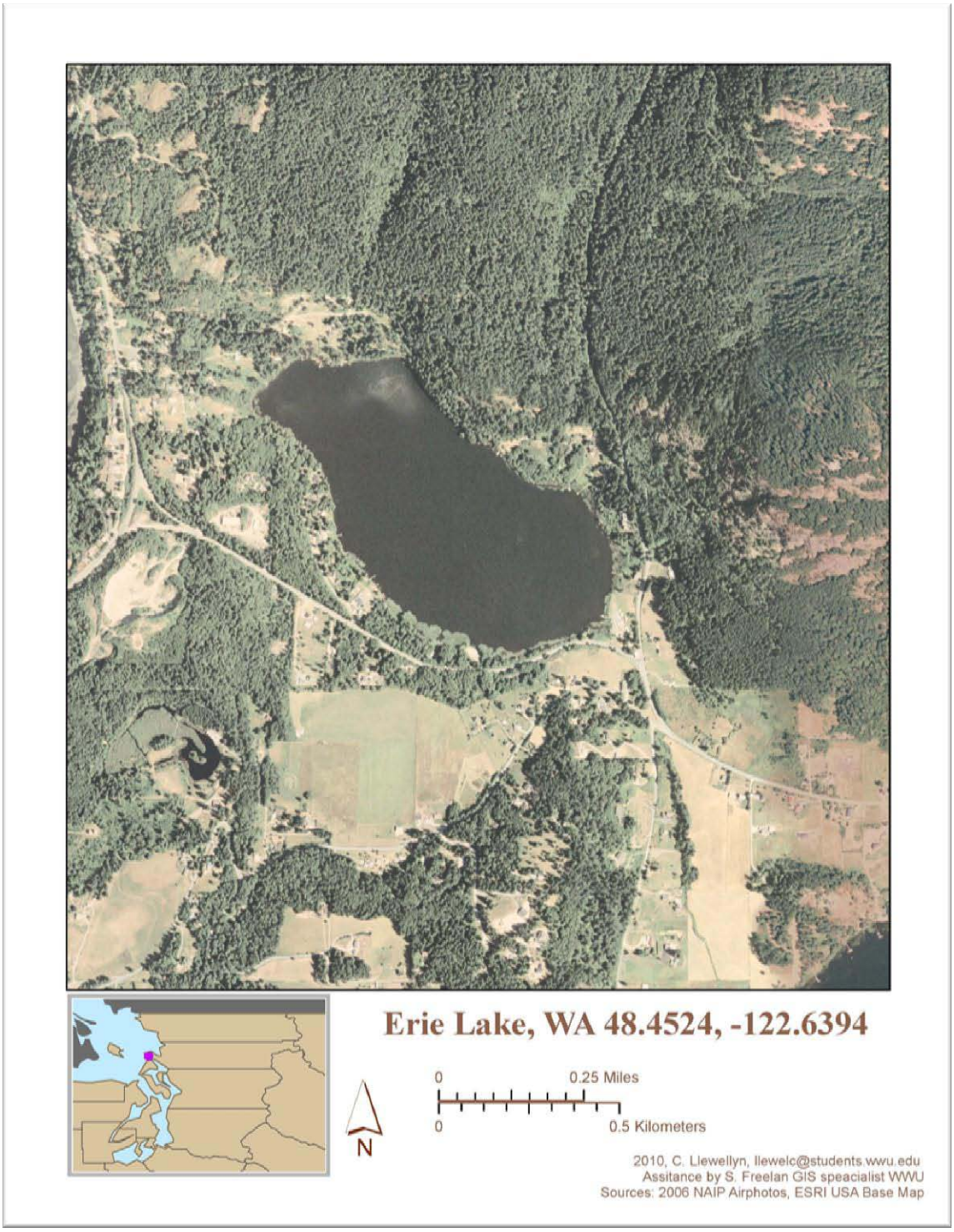


Figure 34. GIS map of Erie Lake, Skagit County, WA

Figure 35. GIS map of Fazon Lake, Whatcom County, WA

Figure 36. GIS map of Lake Goodwin, Snohomish County, WA

Figure 37. GIS map of Lake Goss, Island County, WA

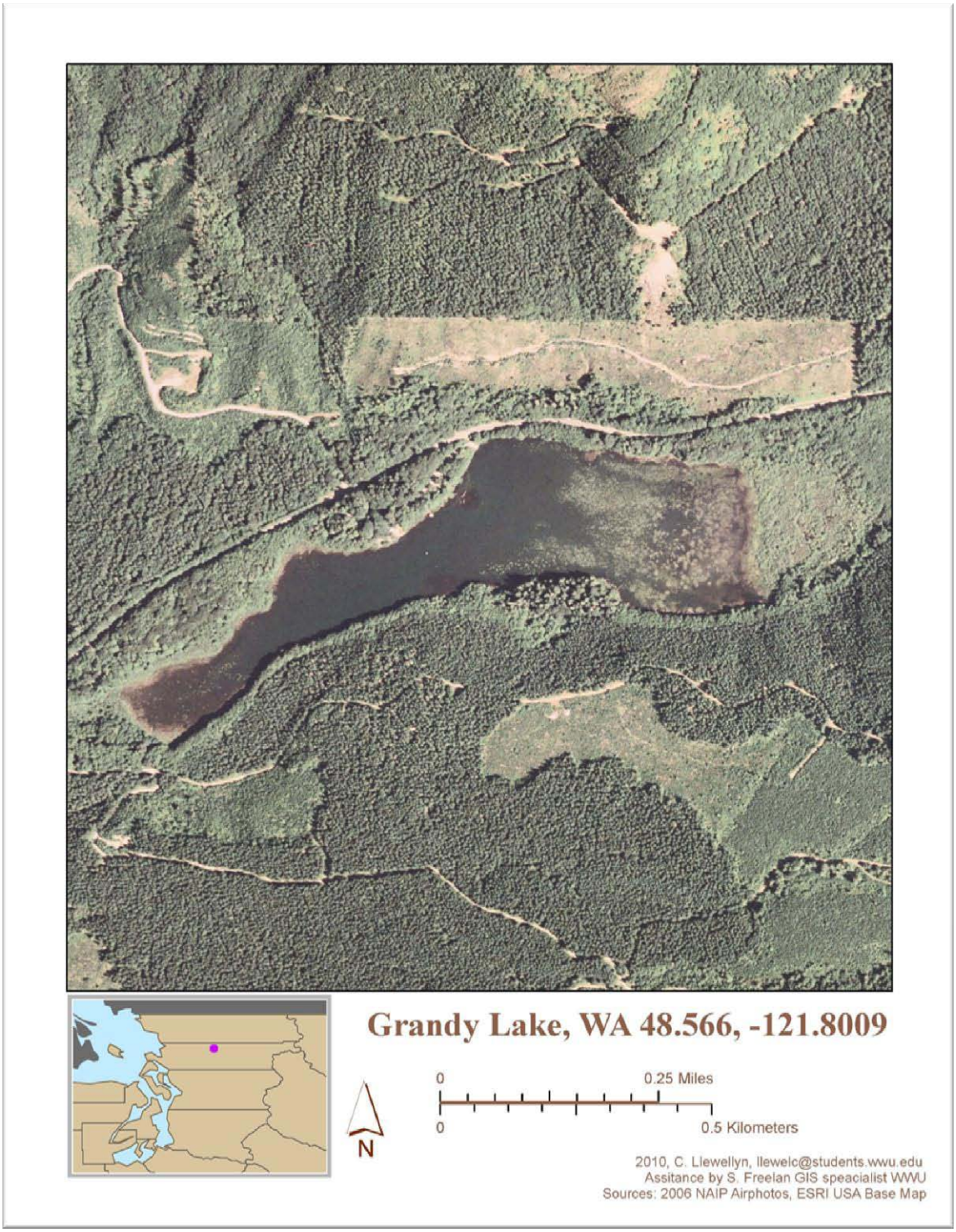


Figure 38. GIS map of Lake Grandy, Skagit County, WA

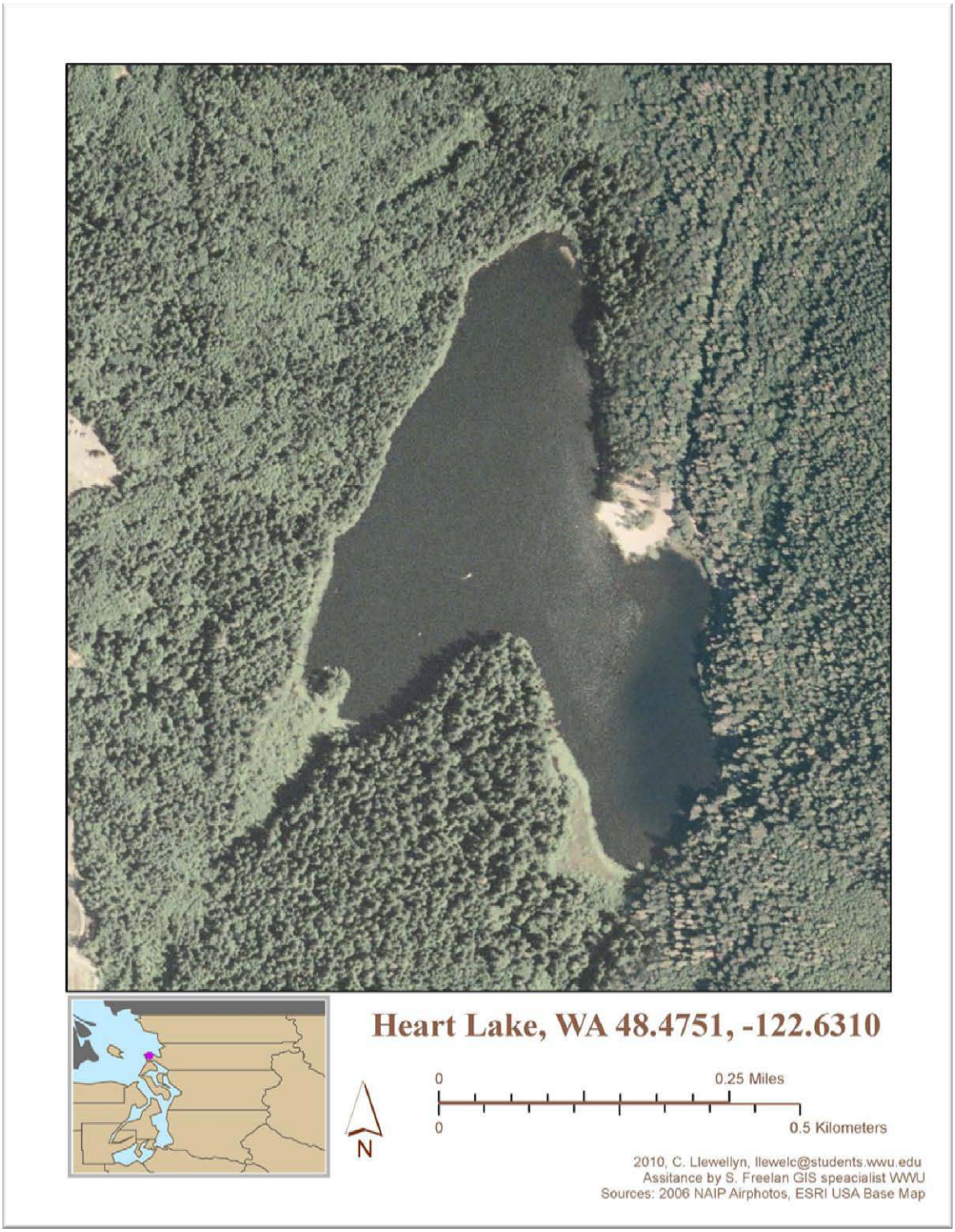


Figure 39. GIS map of Heart Lake, Skagit County, WA

Figure 40. GIS map of Honeymoon Lake, Island County, WA

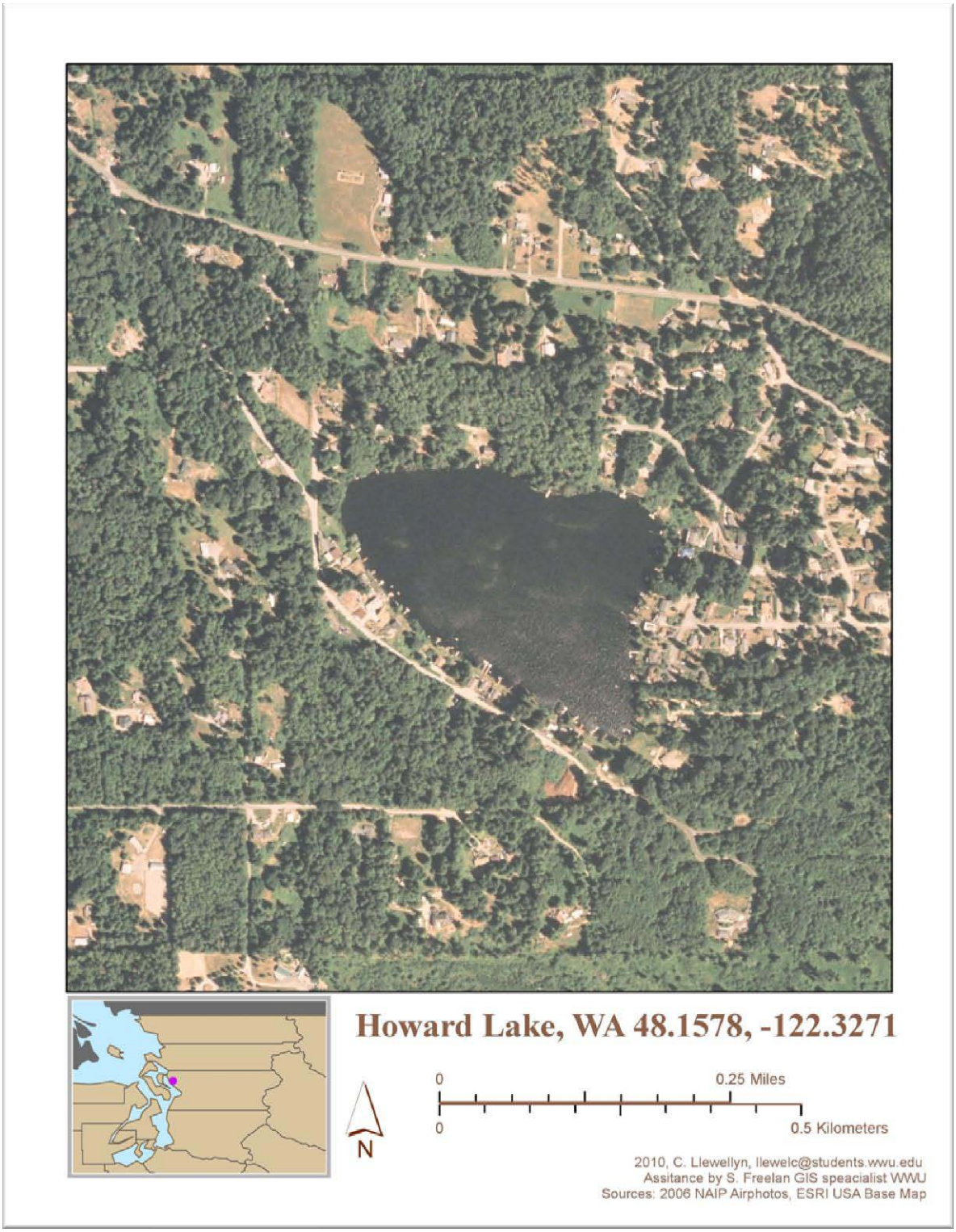


Figure 41. GIS map of Howard Lake, Snohomish County, WA

Figure 42. GIS map of Ketchum Lake, Snohomish County, WA

Figure 43. GIS map of Ki Lake, Snohomish County, WA

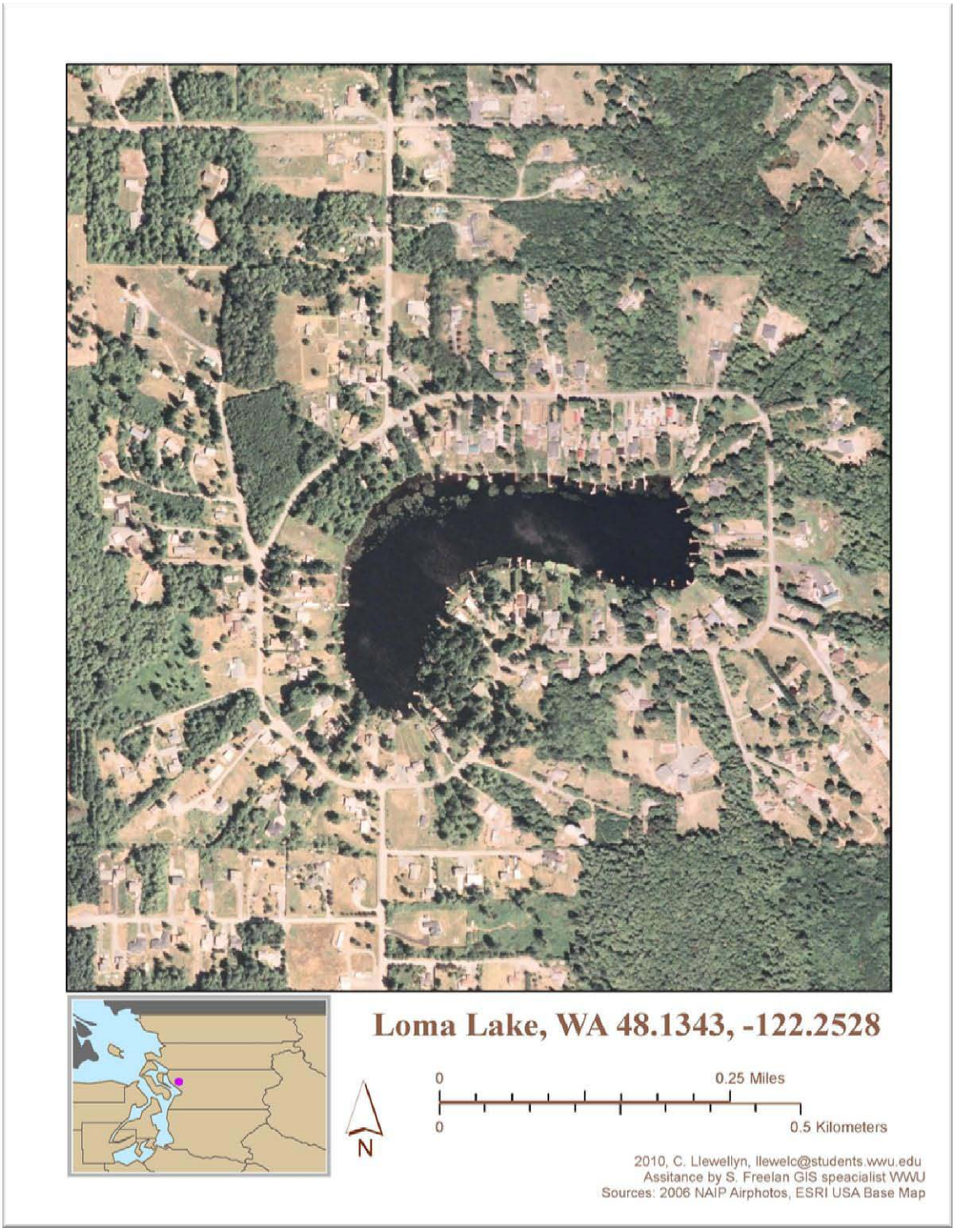


Figure 44. GIS map of Loma Lake, Snohomish County, WA

Figure 45. GIS map of Lone Lake, Island County, WA

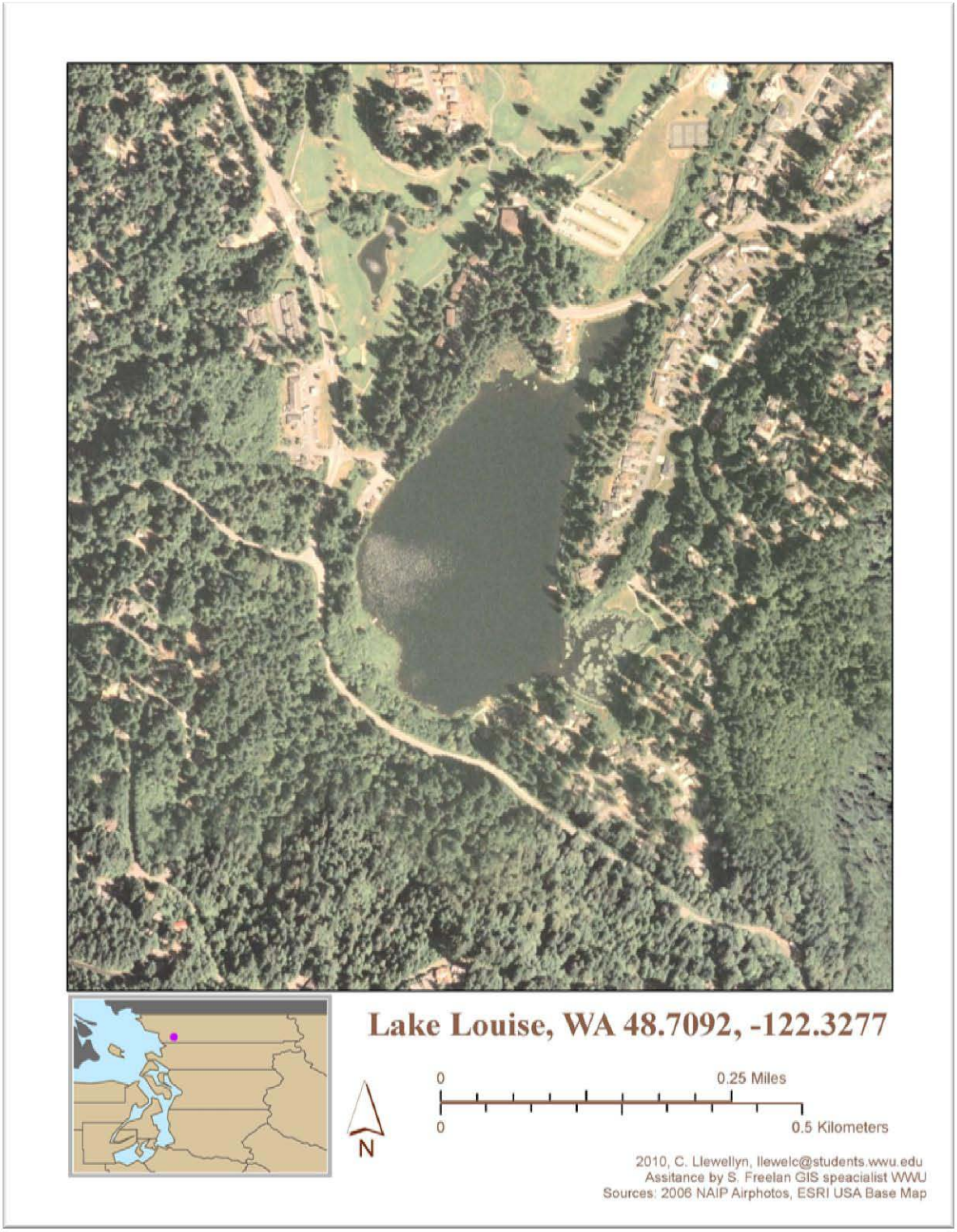


Figure 46. GIS map of Lake Louise, Whatcom County, WA

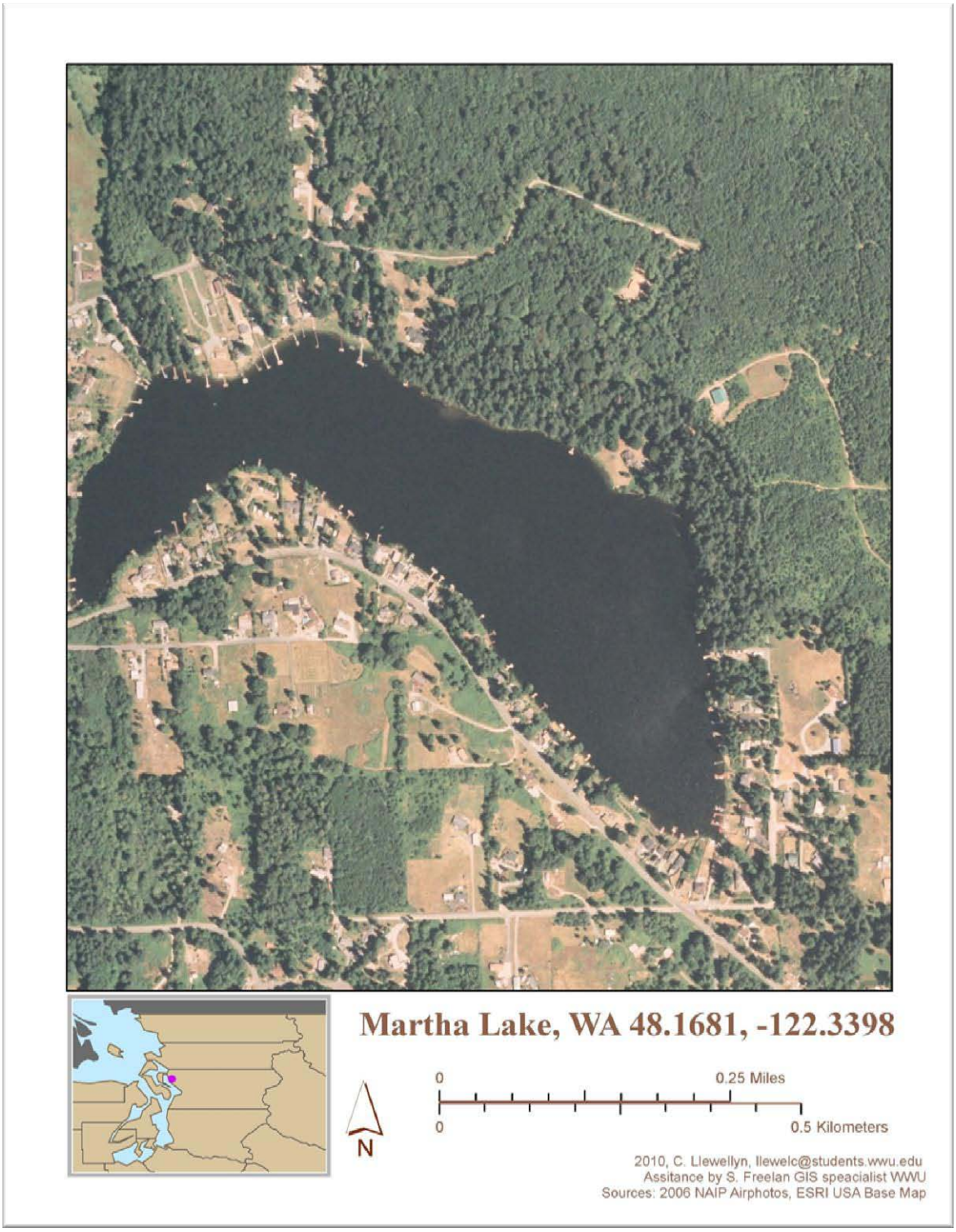


Figure 47. GIS map of Martha Lake, Snohomish County, WA

Figure 48. GIS map of McMurray Lake, Skagit County, WA

Figure 49. GIS map of Mirror Lake, Whatcom County, WA

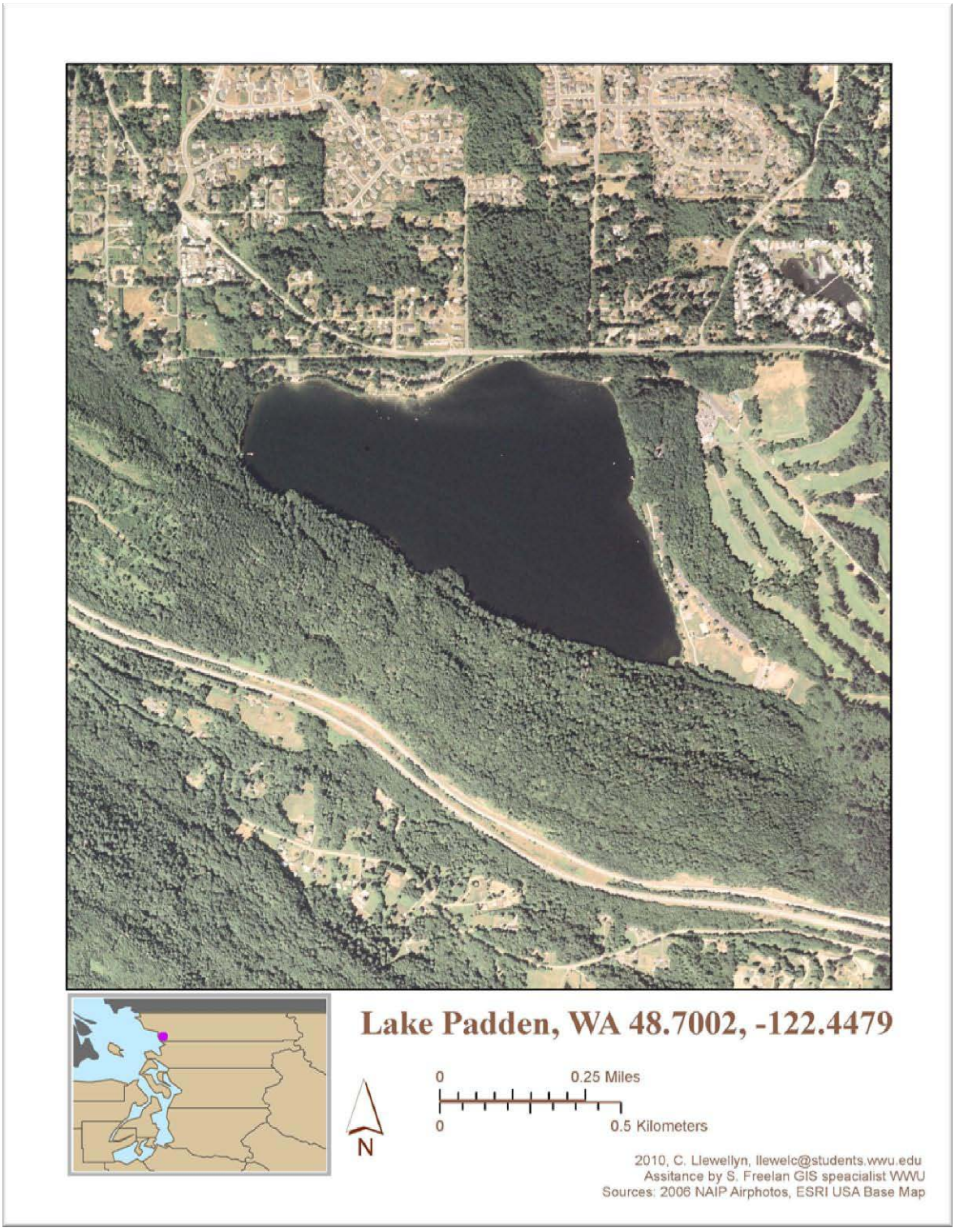


Figure 50. GIS map of Lake Padden, Whatcom County, WA

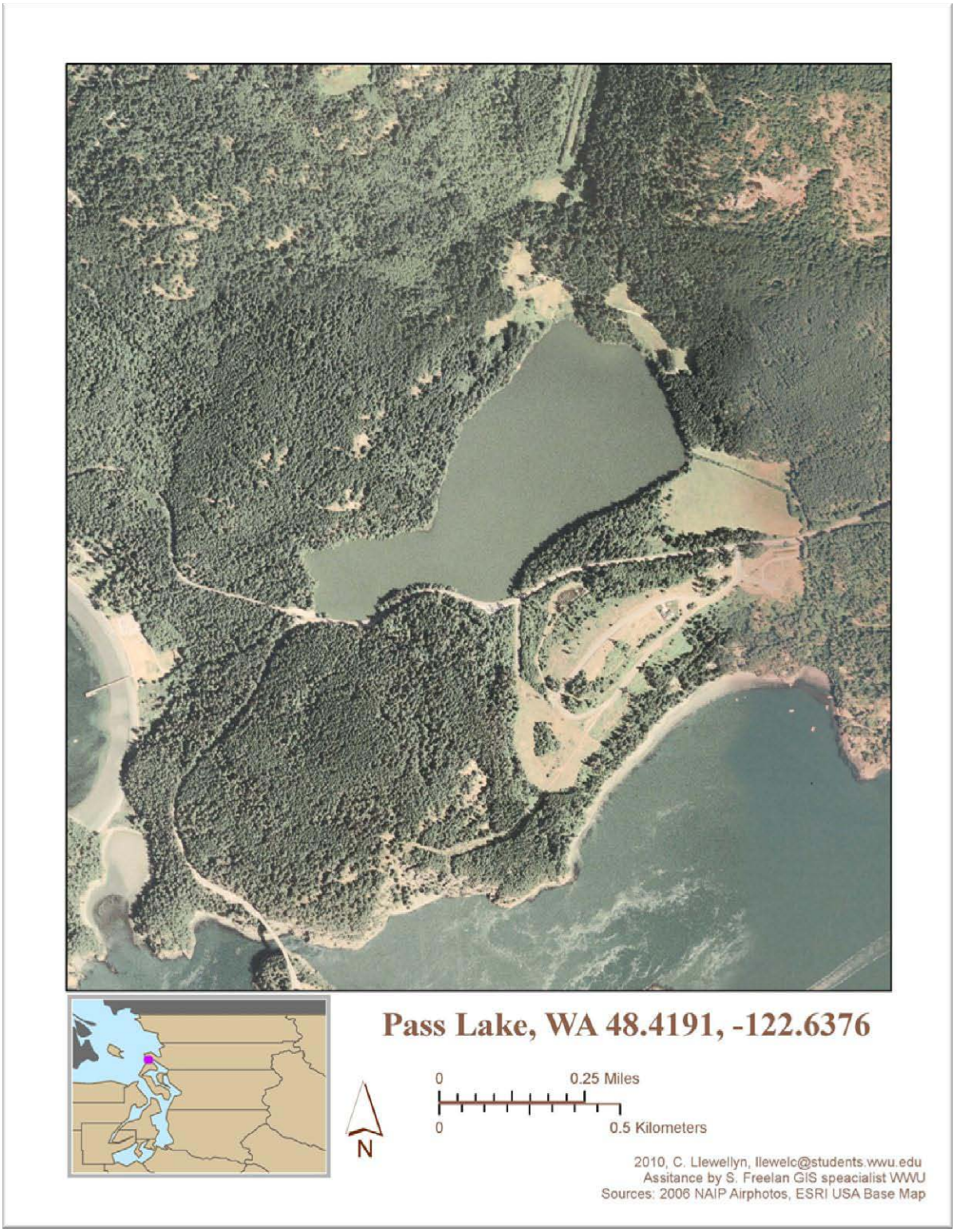


Figure 51. GIS map of Pass Lake, Skagit County, WA

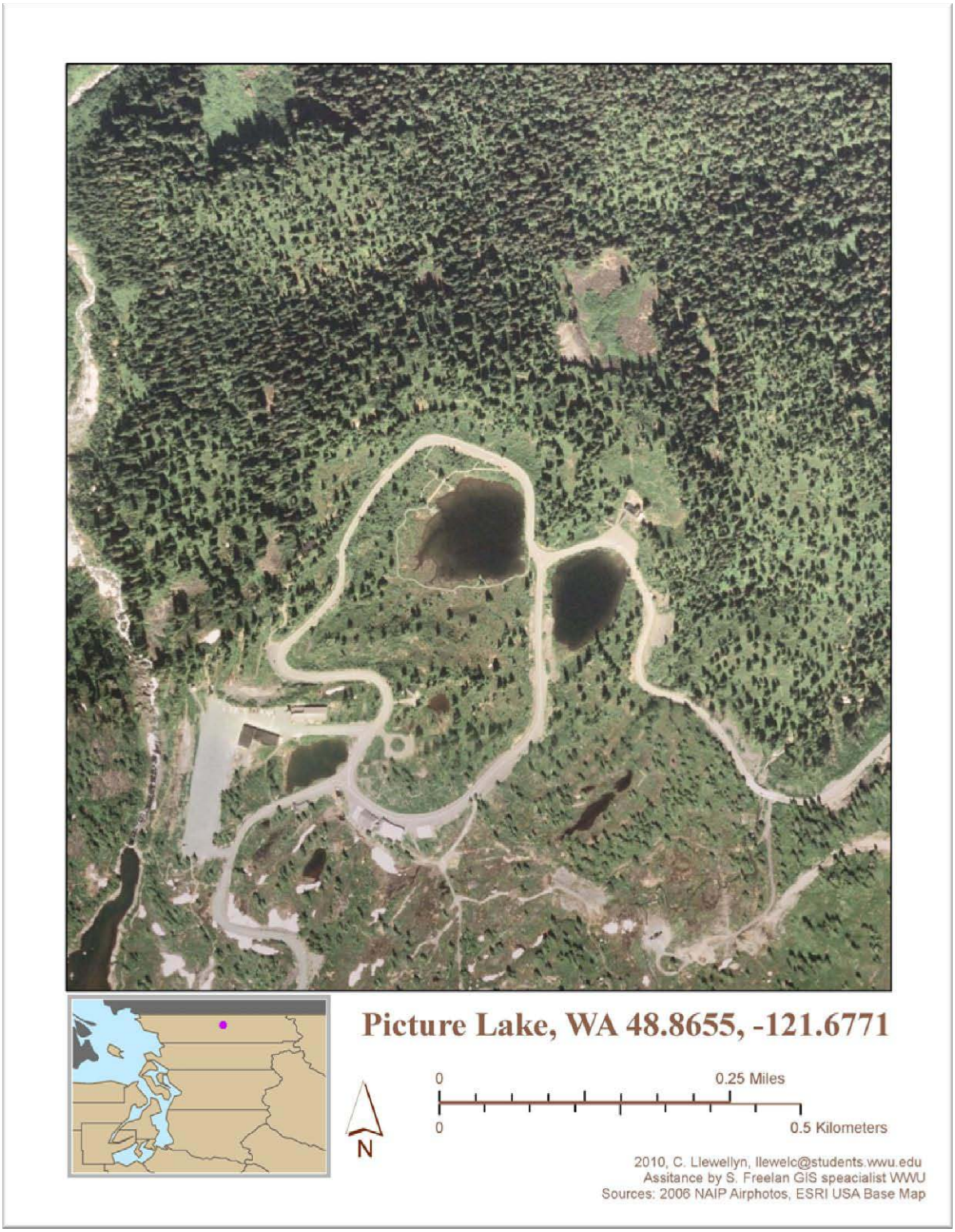


Figure 52. GIS map of Picture Lake, Whatcom County, WA

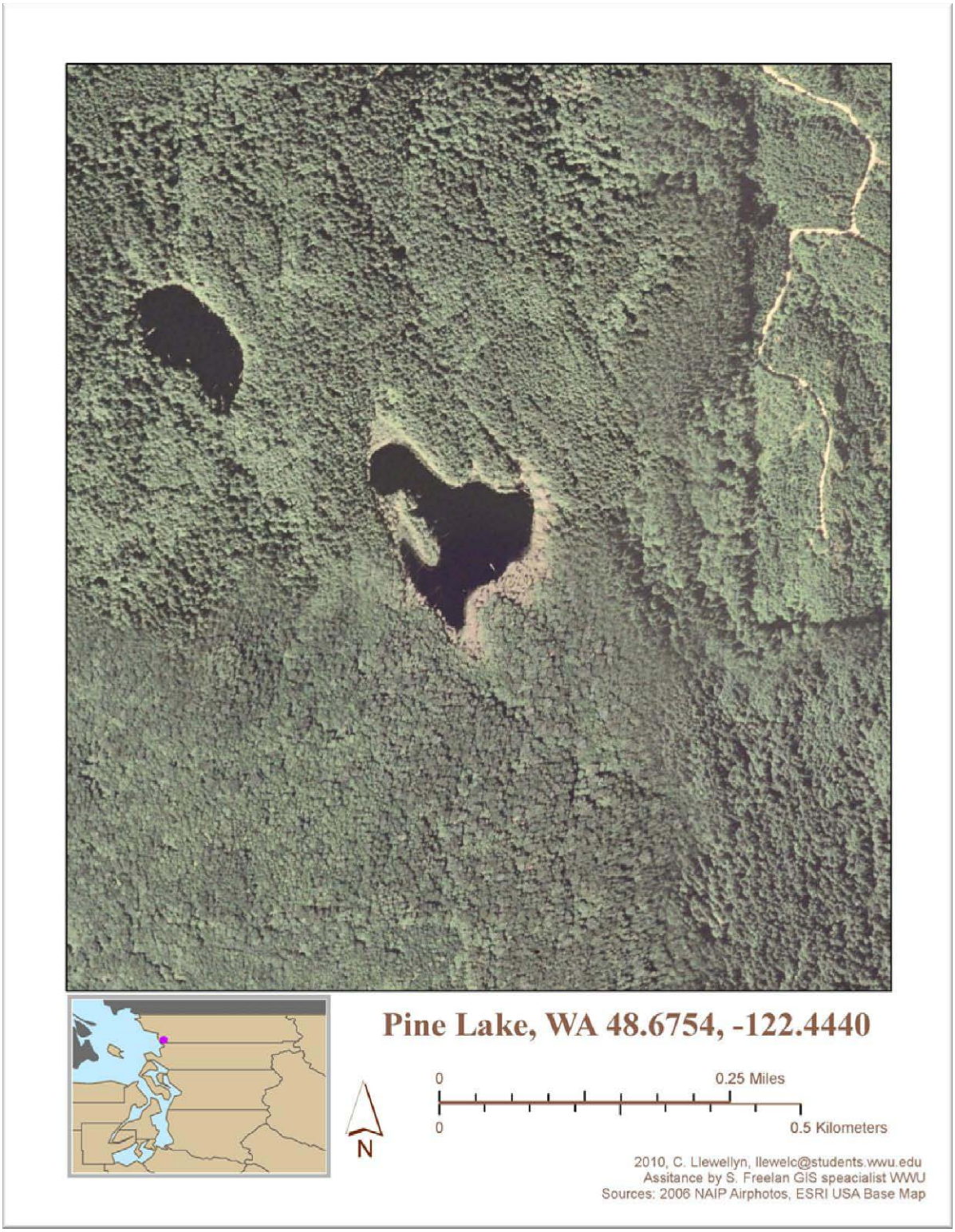


Figure 53. GIS map of Pine Lake, Whatcom County, WA

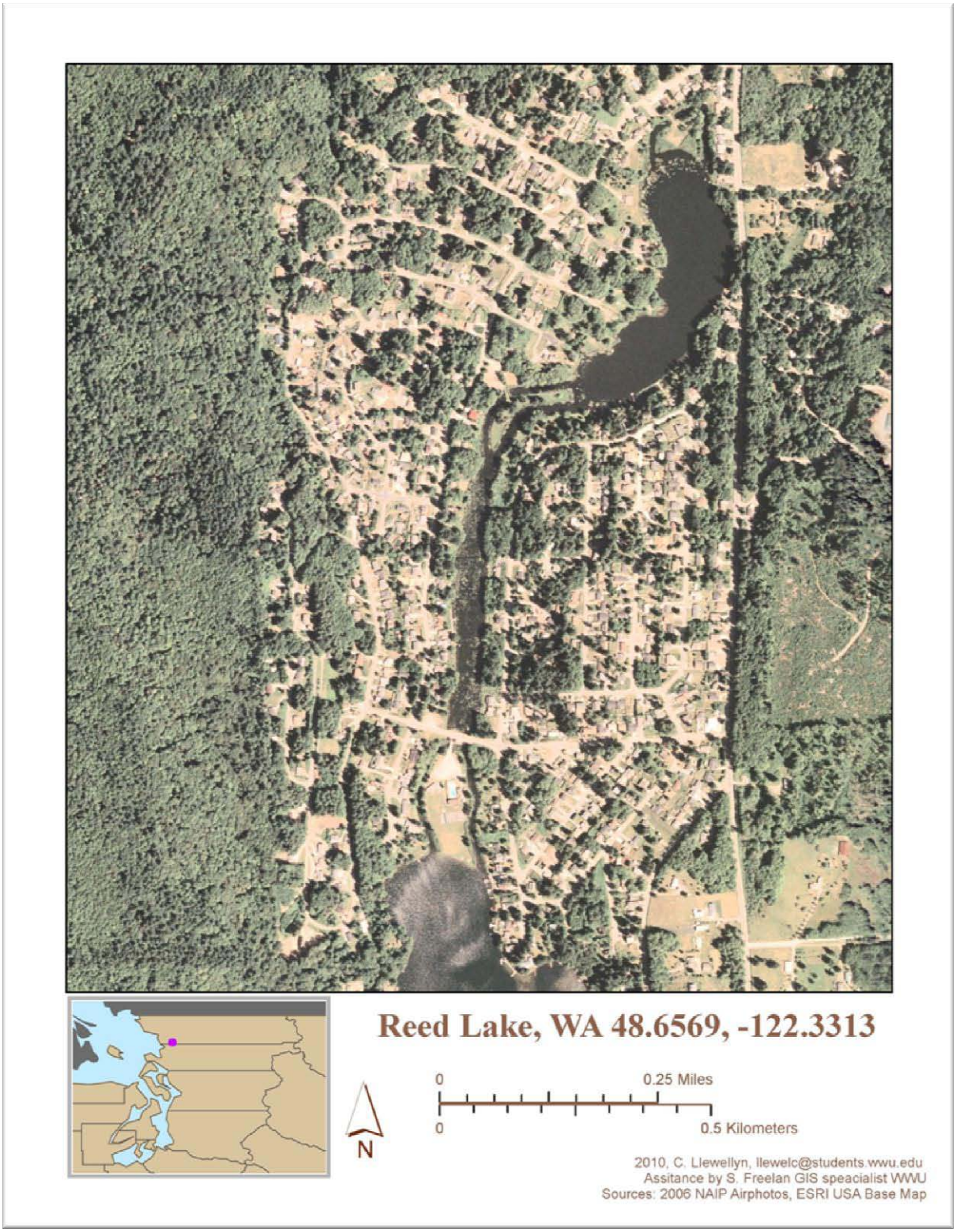


Figure 54. GIS map of Reed Lake, Whatcom County, WA

Figure 55. GIS map of Shoecraft Lake, Snohomish County, WA

Figure 56. GIS map of Silver Lake, Whatcom County, WA

Figure 57. GIS map of Sixteen Lake, Skagit County, WA

Figure 58. GIS map of Squalicum Lake, Whatcom County, WA

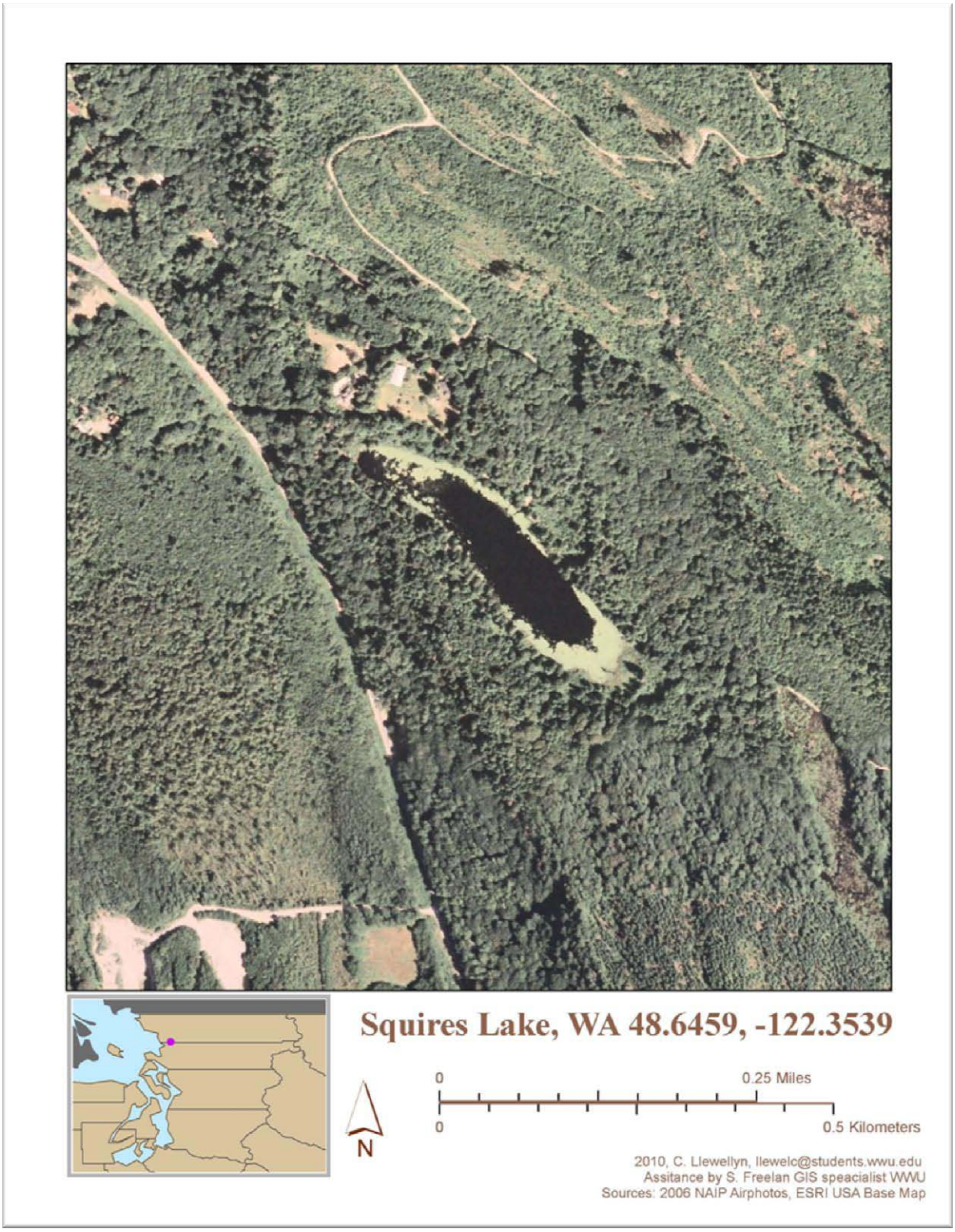


Figure 59. GIS map of Squires Lake, Whatcom/Skagit County, WA

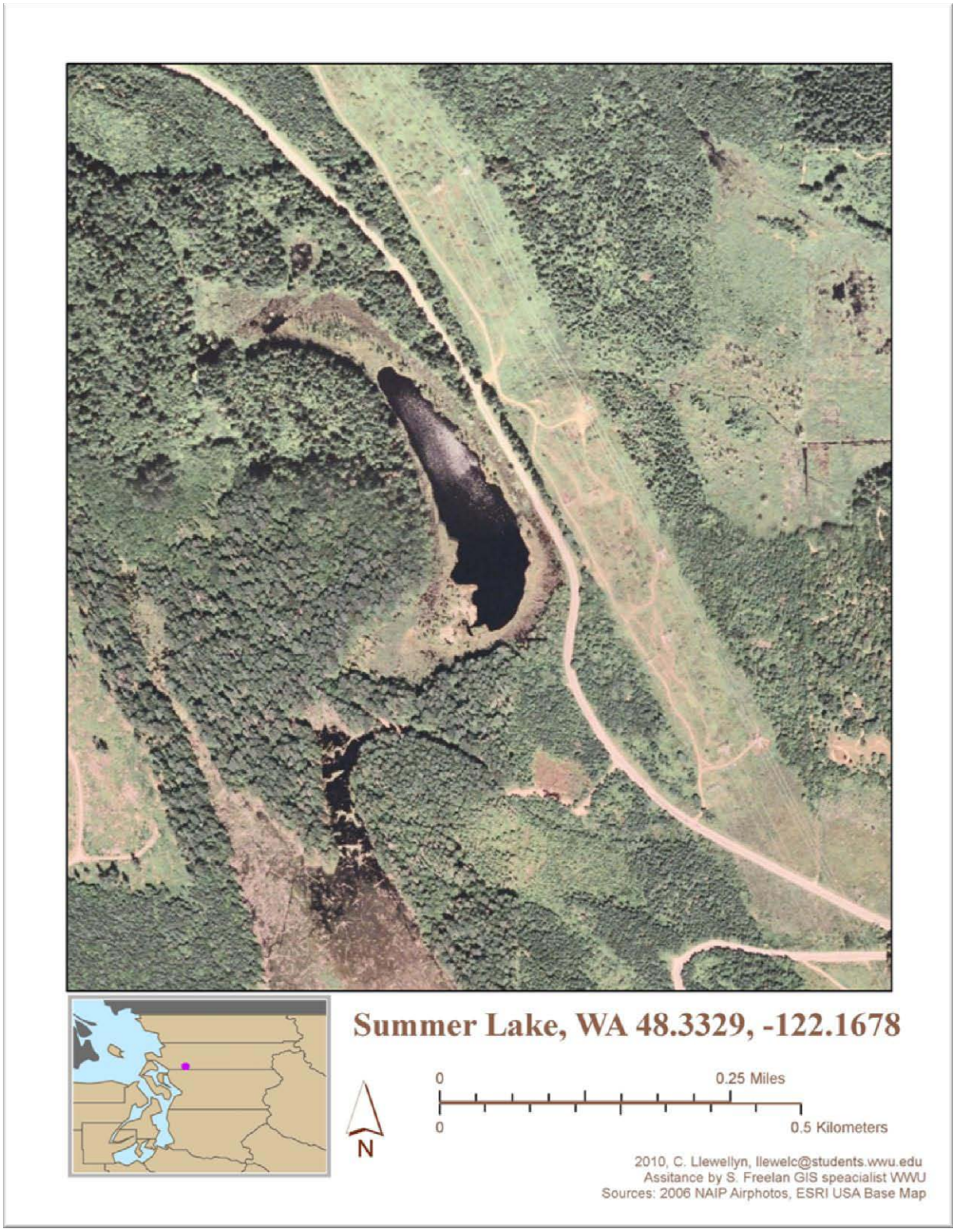


Figure 60. GIS map of Summer Lake, Skagit County, WA

Figure 61. GIS map of Sunday Lake, Snohomish County, WA

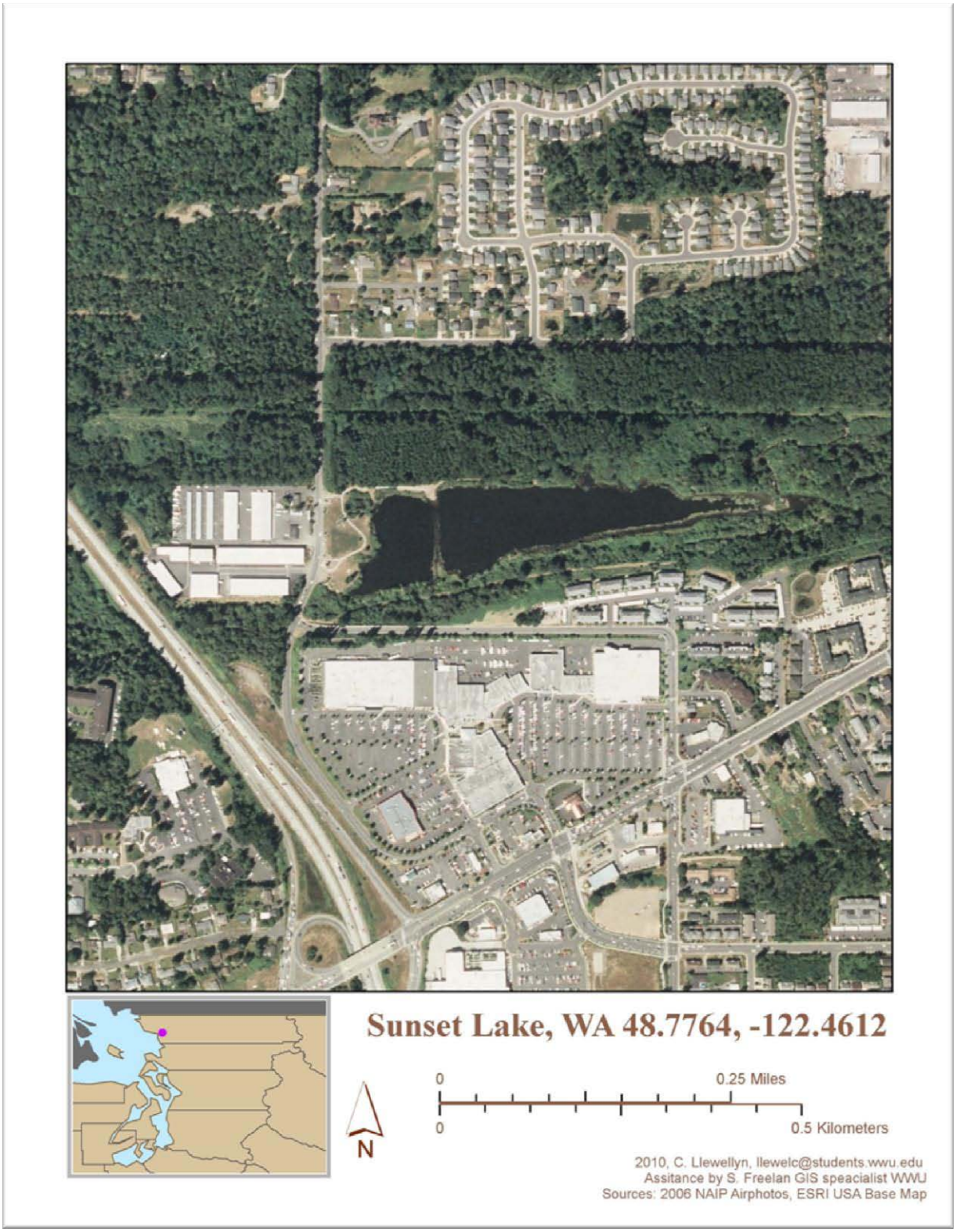


Figure 62. GIS map of Sunset Lake, Whatcom County, WA

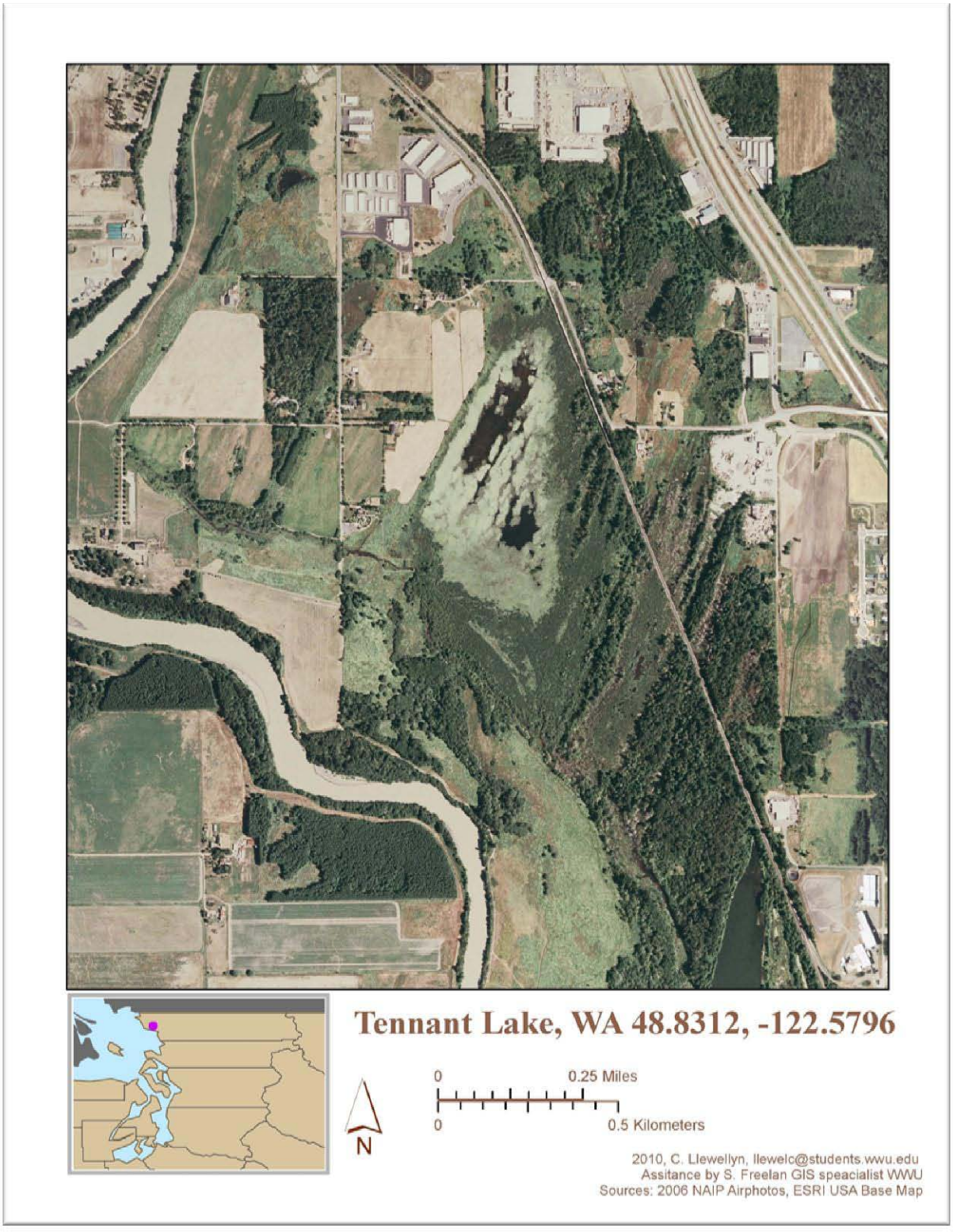


Figure 63. GIS map of Tennant Lake, Whatcom County, WA

Figure 64. GIS map of Lake Terrell, Whatcom County, WA

Figure 65. GIS map of Toad Lake, Whatcom County, WA

Figure 66. GIS map of Lower Twin Lake, Whatcom County, WA

Figure 67. GIS map of Upper Twin Lake, Whatcom County, WA

Figure 68. GIS map of Vogler Lake, Skagit County, WA

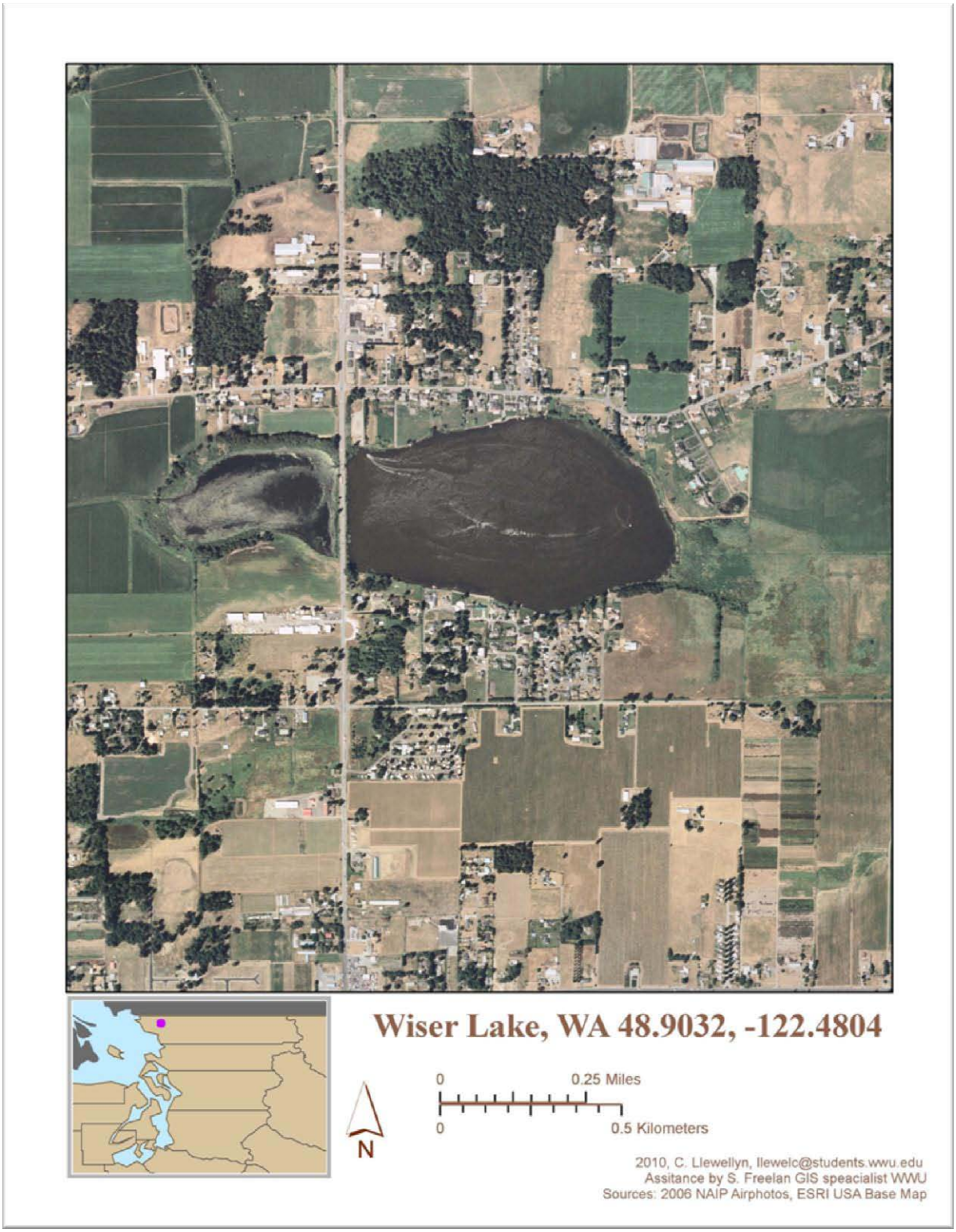


Figure 69. GIS map of Wiser Lake, Whatcom County, WA

Appendix 3.

Statistical Appendix

Table 15. Kendall's tau correlation coefficients between environmental water chemistry variables. Elevation and dissolved oxygen percent saturation were removed from correlation analysis.

Kendall's tau	**DO mg/L**	**Temp (C)**	**pH**	**Conductivity µS/cm**	**Chlorophyll α µg/L**
DO field					
Temperature	0.070				
pH	0.417***	0.361***			
Conductivity	0.118*	0.327***	0.507***		
Chlorophyll α	0.091	0.315***	0.300***	0.417***	
Alkalinity	0.141*	0.308***	0.53***	0.809***	0.434***
Turbidity	0.113*	0.275***	0.291***	0.429***	0.528***
Ammonia	-0.025	0.010	0.072	0.177**	0.034
Total N	-0.069	0.327***	0.297***	0.500***	0.472***
Nitrate	-0.058	-0.143*	-0.130*	-0.233***	-0.218***
Total P	0.024	0.188**	0.142*	0.379***	0.503***
SRP	0.023	0.161**	0.100	0.224***	0.332***
BG dominance	-0.248***	-0.282***	-0.244**	-0.216**	-0.316***

Kendall's tau	**Alkalinity mg$CaCO_3$/L**	**Turbidity (NTU)**	**NH_3 µgN/L**	**TN µgN/L**	**NO_3 µgN/L**	**TP µgP/L**	**SRP µgP/L**
Alkalinity							
Turbidity	0.447***						
Ammonia	0.150**	0.075					
Total N	0.462***	0.460***	0.202***				
Nitrate	-0.195***	-0.136*	0.068	-0.118*			
Total P	0.374***	0.631***	0.081	0.513***	-0.092		
SRP	0.202***	0.284***	0.013	0.243***	-0.081	0.405***	
BG dominance	-0.230**	-0.262***	0.026	-0.256**	0.282***	-0.218**	-0.153

Significance values : *p-value≤0.05, **p-value≤0.01, ***p-value≤0.001. Kendall's tau ≥0.35

Table 16. Summary statistics for the low elevation lakes sampled by the Institute for Watershed Studies for the small lakes monitoring project (2007-2009). The following high elevations lakes were removed from the data set: Picture Lake, Bagley Lake (Upper), Bagley Lake (Lower), Twin Lake (Upper), Twin Lake (Lower), and Canyon Lake.

Lakes	Elev.ft	DO mg/L	Temp (C)	pH	Cond µS/cm	Chl µg/L	Alk $mgCaCO_3/L$	Turb (NTU)	NH_3 µgN/L	TN µgN/L	NO_3 µgN/L	TP µgP/L	SRP µgP/L
mean	341.7	8.449	20.744	7.904	136.626	21.913	41.333	4.066	24.803	664.175	23.266	36.488	9.642
median	**287.5**	**8.275**	**20.6**	**7.85**	**103.5**	**5.7**	**33.8**	**1.65**	**9.85**	**537.5**	**1.45**	**19.7**	**3.8**

Table 17. The data used for my study (organized by year) collected by the Institute for Watershed Studies for their small lakes monitoring project 2007-2009.

Lake	Month	Day	Year	Elev. Ft.	DO mg/L	Temp (C)	pH
Armstrong	8	31	2009	174	9.8	20.6	7.7
Beaver	9	14	2009	30	6	19.8	7.3
Big	8	22	2007	82	9.09	22	7.5
Big	8	20	2008	82	8.08	21.9	7.9
Big	9	14	2009	82	9.6	19.9	8.5
Bug	8	15	2007	107	11.55	24.2	9.3
Bug	8	18	2008	107	5.05	22.2	9.1
Bug	8	18	2009	107	21.5	25.3	10.5
Cain	8	23	2007	391	9.52	20.2	7.8
Cain	8	13	2008	391	8.25	21.5	8.2
Cain	8	10	2009	391	8.8	20.4	8.3
Campbell	8	14	2007	43	7.41	21.3	8.3
Campbell	8	27	2008	43	10.68	20.2	9.2
Campbell	8	24	2009	43	10.7	21.8	8.5
Cavanaugh	8	22	2007	1016	8.89	21.1	7
Cavanaugh	8	20	2008	1016	8.5	19.3	7.4
Cavanaugh	9	14	2009	1016	8.2	20.1	7.4
Cedar	8	14	2008	1542	6.8	19.6	7.17
Clear	8	22	2007	30	6.72	21.5	7
Clear	8	20	2008	30	7.6	21.5	7.5
Clear	9	14	2009	30	6.2	20.5	7.1
Crabapple	9	21	2009	436	7.9	20	7.3
Cranberry	8	14	2007	275	8.03	21	7.7
Cranberry	8	27	2008	275	7.6	20	8
Cranberry	8	24	2009	275	11.6	20.9	9
Deer	8	27	2008	300	8.6	20	7.5
Deer	8	24	2009	300	9.1	21.6	7.8
Erie	8	14	2007	90	8.9	20.9	8.5
Erie	8	27	2008	90	8.87	19.5	8.9
Erie	8	24	2009	90	9.7	21.8	8.2
Fazon	8	15	2007	128	4.77	22.2	7
Fazon	8	11	2008	128	7.14	22.5	7.6
Goodwin	9	21	2009	318	8.1	20.7	7.8
Goss	8	27	2008	62	8.37	20.5	8
Goss	8	24	2009	62	9.4	21.4	8.1

Lake	Month	Day	Year	Elev. Ft.	DO mg/L	Temp (C)	pH
Grandy	9	8	2009	804	8.9	18.8	7.9
Heart	8	14	2007	325	8.18	20.7	7.7
Heart	8	27	2008	325	7.83	19.7	8.3
Heart	8	24	2009	325	11.4	22.5	9.1
Honeymoon	8	24	2009	43	8.7	20.3	7.8
Howard	9	21	2009	246	8.2	19.4	7.9
Ketchum	8	31	2009	226	15.3	20.9	9.9
Ki	9	21	2009	436	8.2	20.9	7.3
Loma	9	21	2009	564	8	20.7	7
Lone	8	27	2008	0	5.13	19.8	8
Lone	8	24	2009	0	14.6	21.8	9.6
Louise	8	23	2007	412	8.81	21.6	7.7
Louise	8	13	2008	412	8.13	22.3	7.7
Louise	8	10	2009	412	8.2	20.6	7.8
Martha	9	21	2009	207	8.9	19.7	7.9
McMurray	8	22	2007	232	10.66	21.2	8.5
McMurray	8	20	2008	232	9.04	22	8.7
McMurray	9	14	2009	232	8.2	20.2	8
Mirror	8	23	2007	350	8.51	18.5	7
Mirror	8	13	2008	350	9.39	15.8	7
Mirror	8	10	2009	350	7.7	20.4	7.3
Padden	8	23	2007	438	8.3	20.6	7.5
Padden	8	18	2008	438	8.77	22.8	8.2
Padden	8	10	2009	438	8.2	21	8.2
Pass	8	14	2007	130	9.66	20.1	8.4
Pass	8	27	2008	130	8.75	20	8.6
Pass	8	24	2009	130	9.7	20.3	8.5
Pine	8	14	2008	1617	7.35	21	7.11
Reed	8	23	2007	365	8.22	19.7	7
Reed	8	13	2008	365	7.8	21.3	7.5
Reed	8	10	2009	365	5.6	18.8	6.8
Shoecraft	9	21	2009	331	8.4	17.2	7.9
Silver	8	19	2007	765	8.8	20.1	7.6
Silver	8	25	2008	765	8.23	19.7	7.9
Silver	9	8	2009	765	7.5	18.9	8.1
Sixteen	9	14	2009	436	7.5	19.3	7.3
Squalicum	8	15	2007	477	7.16	20.6	7
Squalicum	8	18	2008	477	4.48	23	6.8

Lake	Month	Day	Year	Elev. Ft.	DO mg/L	Temp (C)	pH
Squalicum	8	18	2009	477	5.2	23.4	7
Squires	8	23	2007	420	2.65	19.8	6.1
Squires	8	13	2008	420	6.44	20.3	6.9
Squires	8	10	2009	420	3	19.7	6.6
Summer	9	14	2009	531	6.5	19.1	6.7
Sunday	8	31	2009	223	7.3	21.1	7.7
Sunset	8	15	2007	133	15.46	22.9	9.3
Sunset	8	18	2008	133	8.47	23.8	8.8
Sunset	8	18	2009	133	11.3	23.8	9
Tennant	8	15	2007	0	0.54	16.3	6.3
Tennant	8	11	2008	0	1.54	16.3	6.8
Terrell	8	15	2007	210	11.19	22.9	8.8
Terrell	8	11	2008	210	7.95	19.7	8.9
Toad	8	22	2007	806	9.68	20.3	8.5
Toad	8	18	2008	806	8.43	22.4	8.2
Toad	8	18	2009	806	10.3	22.8	9.1
Vogler	9	8	2009	1079	7.7	18.5	6.4
Wiser	8	15	2007	70	10.99	23.3	8.5
Wiser	8	11	2008	70	9.31	22	9

Lake	Month	Day	Year	Cond µS/cm	Chl µg/L	Alk $mgCaCO_3/L$
Armstrong	8	31	2009	67.8	5.1	28.3
Beaver	9	14	2009	127	66	55.5
Big	8	22	2007	99.4	27.8	37.8
Big	8	20	2008	101.5	15.96	38.9
Big	9	14	2009	102	21.3	38.3
Bug	8	15	2007	159.7	4.3	68.5
Bug	8	18	2008	123.2	25.75	49.6
Bug	8	18	2009	177	5.7	53
Cain	8	23	2007	58.9	6.1	17.9
Cain	8	13	2008	63.4	2.72	18.3
Cain	8	10	2009	60.2	3	18.3
Campbell	8	14	2007	268	45.3	74.6
Campbell	8	27	2008	275	87.88	88.5
Campbell	8	24	2009	278	26.6	92.3
Cavanaugh	8	22	2007	29.3	5.6	9.2

Lake	Month	Day	Year	Cond µS/cm	Chl µg/L	Alk $mgCaCO_3/L$
Cavanaugh	8	20	2008	30.9	3.01	9.4
Cavanaugh	9	14	2009	30.5	1.9	10.3
Cedar	8	14	2008	55.3	1.35	14.6
Clear	8	22	2007	86.2	7	32.4
Clear	8	20	2008	87.6	3.94	32
Clear	9	14	2009	90.7	5	32.9
Crabapple	9	21	2009	57.6	4.2	10.8
Cranberry	8	14	2007	278	29.5	65
Cranberry	8	27	2008	282	7.08	35.4
Cranberry	8	24	2009	286	13.6	65.7
Deer	8	27	2008	83	1.89	21
Deer	8	24	2009	84.2	2.4	21.4
Erie	8	14	2007	260	12.2	77.1
Erie	8	27	2008	250	3.77	70.1
Erie	8	24	2009	256	10.3	69.9
Fazon	8	15	2007	324	10.2	51.6
Fazon	8	11	2008	446	35.93	52.1
Goodwin	9	21	2009	101	2.5	33.9
Goss	8	27	2008	129	2	33.2
Goss	8	24	2009	133	1.9	34.4
Grandy	9	8	2009	136	8.5	64.8
Heart	8	14	2007	239	13.2	73.8
Heart	8	27	2008	236	17.67	75.1
Heart	8	24	2009	235	13.4	74.9
Honeymoon	8	24	2009	229	5.1	79.5
Howard	9	21	2009	125	2.5	46.6
Ketchum	8	31	2009	168	323	47.1
Ki	9	21	2009	46.6	1.5	9.3
Loma	9	21	2009	57.4	8.3	9.4
Lone	8	27	2008	193	32.41	68.8
Lone	8	24	2009	196	596	67.1
Louise	8	23	2007	68.1	10.9	23.3
Louise	8	13	2008	71.4	4.12	24.3
Louise	8	10	2009	73.9	3.2	23.1
Martha	9	21	2009	110	4.2	32.6

Lake	Month	Day	Year	Cond µS/cm	Chl µg/L	Alk $mgCaCO_3/L$
McMurray	8	22	2007	101.4	12.4	33.2
McMurray	8	20	2008	102.6	4.68	33.3
McMurray	9	14	2009	104	3.8	33.7
Mirror	8	23	2007	57.9	7.8	16.4
Mirror	8	13	2008	55.5	0.94	13.6
Mirror	8	10	2009	56.4	3.5	21.8
Padden	8	23	2007	97.3	4.8	27.1
Padden	8	18	2008	104.4	4.41	30.9
Padden	8	10	2009	103	4.8	28.8
Pass	8	14	2007	291	41.2	79.6
Pass	8	27	2008	288	9.92	76.3
Pass	8	24	2009	294	11.2	77.4
Pine	8	14	2008	42.2	1.27	9.8
Reed	8	23	2007	55.2	2.5	18.9
Reed	8	13	2008	51.1	3.34	16.3
Reed	8	10	2009	50	2.8	15.5
Shoecraft	9	21	2009	114	2.2	41
Silver	8	19	2007	141	5.2	55.3
Silver	8	25	2008	136.7	3.8	53.7
Silver	9	8	2009	138	1.3	51.1
Sixteen	9	14	2009	90.7	3.1	32.4
Squalicum	8	15	2007	67.9	6.3	26.7
Squalicum	8	18	2008	77.1	1.76	29.8
Squalicum	8	18	2009	68.3	6.5	25.8
Squires	8	23	2007	42.5	15.7	15.5
Squires	8	13	2008	44.7	54.55	16.8
Squires	8	10	2009	46.3	4.1	17.7
Summer	9	14	2009	34.1	8.2	10.3
Sunday	8	31	2009	96.1	5.7	27.2
Sunset	8	15	2007	175.8	44.6	80
Sunset	8	18	2008	152.7	9.61	64
Sunset	8	18	2009	156	11.6	66.8
Tennant	8	15	2007	122.8	21.4	50.4
Tennant	8	11	2008	151.2	2.1	50.4
Terrell	8	15	2007	90.9	35.5	31.8

Lake	Month	Day	Year	Cond µS/cm	Chl µg/L	Alk $mgCaCO_3/L$
Terrell	8	11	2008	90.7	1.66	29.5
Toad	8	22	2007	110.5	15.9	45
Toad	8	18	2008	116.6	4.65	47
Toad	8	18	2009	120	5.9	47.3
Vogler	9	8	2009	15.2	1.6	9.8
Wiser	8	15	2007	394	64.6	82.2
Wiser	8	11	2008	396	6.38	80.7

Lake	Month	Day	Year	Turb (NTU)	NH_3 µgN/L	TN µgN/L
Armstrong	8	31	2009	0.7	6.5	520
Beaver	9	14	2009	30.6	5.4	1669
Big	8	22	2007	4.6	4.7	367.9
Big	8	20	2008	4.3	6.4	416.9
Big	9	14	2009	5.4	6.4	567
Bug	8	15	2007	2.0	9.5	658.6
Bug	8	18	2008	3.9	5	942
Bug	8	18	2009	3.9	12.6	879
Cain	8	23	2007	0.7	9.2	691.1
Cain	8	13	2008	0.7	4.3	830.4
Cain	8	10	2009	0.6	7.1	822
Campbell	8	14	2007	18.6	12.1	1341.5
Campbell	8	27	2008	25.4	16.9	1498.4
Campbell	8	24	2009	8.6	6.6	1198
Cavanaugh	8	22	2007	0.8	9.1	171.4
Cavanaugh	8	20	2008	1.5	21.5	227.6
Cavanaugh	9	14	2009	0.8	13.3	161
Cedar	8	14	2008	0.4	10.6	425.2
Clear	8	22	2007	1.1	4.6	367.7
Clear	8	20	2008	1.0	8.6	287
Clear	9	14	2009	2.9	3.3	486
Crabapple	9	21	2009	0.8	26	529
Cranberry	8	14	2007	2.3	16.4	870.1
Cranberry	8	27	2008	1.1	18.3	766.5
Cranberry	8	24	2009	2.5	7.6	985
Deer	8	27	2008	0.6	9.5	413.9

Lake	Month	Day	Year	Turb (NTU)	NH_3 µgN/L	TN µgN/L
Deer	8	24	2009	0.7	24.7	463
Erie	8	14	2007	2.3	21.9	828.3
Erie	8	27	2008	1.6	17.4	725.4
Erie	8	24	2009	2.5	12.3	988
Fazon	8	15	2007	1.2	776.7	1827.2
Fazon	8	11	2008	7.0	6.1	1215.2
Goodwin	9	21	2009	0.6	13.4	453
Goss	8	27	2008	0.8	11.4	337.7
Goss	8	24	2009	0.3	4.5	390
Grandy	9	8	2009	4.1	18.7	414
Heart	8	14	2007	2.7	11.4	639.8
Heart	8	27	2008	4.8	17.8	688.6
Heart	8	24	2009	3.5	7.7	847
Honeymoon	8	24	2009	2.0	6	723
Howard	9	21	2009	0.7	14.7	423
Ketchum	8	31	2009	13.3	8	1571
Ki	9	21	2009	0.6	30.2	350
Loma	9	21	2009	1.9	38.6	652
Lone	8	27	2008	4.5	389	1466.1
Lone	8	24	2009	32.8	10	2671
Louise	8	23	2007	1.1	1.1	283
Louise	8	13	2008	1.7	7	327.5
Louise	8	10	2009	0.8	7.5	282
Martha	9	21	2009	1.3	22.6	432
McMurray	8	22	2007	1.8	15.6	366.3
McMurray	8	20	2008	1.1	14.7	328.2
McMurray	9	14	2009	0.7	2.9	243
Mirror	8	23	2007	24.0	0	149.9
Mirror	8	13	2008	10.7	1.8	97.7
Mirror	8	10	2009	1.3	1.3	347
Padden	8	23	2007	0.7	15.6	348.5
Padden	8	18	2008	2.0	3	338.6
Padden	8	10	2009	1.2	7.4	337
Pass	8	14	2007	6.7	9.7	793.2
Pass	8	27	2008	4.1	20.7	655.7
Pass	8	24	2009	3.6	8.4	737

Lake	Month	Day	Year	Turb (NTU)	NH_3 µgN/L	TN µgN/L
Pine	8	14	2008	0.4	10.4	425.8
Reed	8	23	2007	1.1	17.2	380.4
Reed	8	13	2008	1.4	7	397.3
Reed	8	10	2009	2.7	73.3	546
Shoecraft	9	21	2009	0.9	18.4	449
Silver	8	19	2007	0.7	28.7	208.8
Silver	8	25	2008	3.5	12.8	250.1
Silver	9	8	2009	0.6	12.3	220
Sixteen	9	14	2009	0.7	11.3	323
Squalicum	8	15	2007	1.2	10.7	762.6
Squalicum	8	18	2008	1.6	10.6	929.6
Squalicum	8	18	2009	7.1	5.8	1105
Squires	8	23	2007	0.6	4.4	389.1
Squires	8	13	2008	4.4	13.5	751.2
Squires	8	10	2009	0.8	3.5	402
Summer	9	14	2009	0.6	5.6	369
Sunday	8	31	2009	1.6	10.2	752
Sunset	8	15	2007	9.4	6.6	751.1
Sunset	8	18	2008	4.3	5.2	607.5
Sunset	8	18	2009	4.7	5.1	550
Tennant	8	15	2007	5.5	38.2	1143.1
Tennant	8	11	2008	1.7	26.6	928
Terrell	8	15	2007	5.8	11.7	1007.4
Terrell	8	11	2008	1.4	8	812.8
Toad	8	22	2007	1.5	0.1	406.2
Toad	8	18	2008	1.8	30.2	505
Toad	8	18	2009	1.5	6.6	396
Vogler	9	8	2009	1.2	9.1	597
Wiser	8	15	2007	21.9	28.8	1787.1
Wiser	8	11	2008	7.2	8.7	1119.9

Lake	Month	Day	Year	NO_3 µgN/L	TP µgP/L	SRP µgP/L
Armstrong	8	31	2009	2.4	16.9	8.2
Beaver	9	14	2009	1	139	8.1
Big	8	22	2007	0.5	21.7	7.7
Big	8	20	2008	4.7	22.5	3.4

Lake	Month	Day	Year	NO_3 µgN/L	TP µgP/L	SRP µgP/L
Big	9	14	2009	4.5	26.5	12.6
Bug	8	15	2007	1.5	21.8	3.2
Bug	8	18	2008	2.9	37.9	7.4
Bug	8	18	2009	1.4	55.8	15.6
Cain	8	23	2007	430.1	12.8	3
Cain	8	13	2008	561.6	3.1	7.1
Cain	8	10	2009	515	7.7	4.5
Campbell	8	14	2007	1.6	49.4	3.7
Campbell	8	27	2008	5	82.2	0.2
Campbell	8	24	2009	0	52.3	5.3
Cavanaugh	8	22	2007	16.1	18.8	2.3
Cavanaugh	8	20	2008	50	10.4	0.8
Cavanaugh	9	14	2009	3.2	10.5	2.8
Cedar	8	14	2008	115.9	4.1	2.7
Clear	8	22	2007	0.9	22.6	3.1
Clear	8	20	2008	1.9	11.5	2
Clear	9	14	2009	0	17	2.6
Crabapple	9	21	2009	42.3	4.4	1.6
Cranberry	8	14	2007	1.1	36.4	7.8
Cranberry	8	27	2008	0.8	30.8	4.6
Cranberry	8	24	2009	0.3	27.2	3.7
Deer	8	27	2008	0.5	5.6	0.2
Deer	8	24	2009	5	8.7	3.9
Erie	8	14	2007	1.1	17.8	2.4
Erie	8	27	2008	0.9	20	0.6
Erie	8	24	2009	0	21	3.2
Fazon	8	15	2007	11.5	62	22.2
Fazon	8	11	2008	0.1	127.3	51.4
Goodwin	9	21	2009	0.7	0.7	2.4
Goss	8	27	2008	0.7	9.9	0.2
Goss	8	24	2009	1.3	5.1	1.8
Grandy	9	8	2009	2.8	27.6	6.8
Heart	8	14	2007	3	30.1	9.8
Heart	8	27	2008	1.3	43.7	5.9
Heart	8	24	2009	0.3	25.4	3.6
Honeymoon	8	24	2009	0	33	14.3

Lake	Month	Day	Year	NO_3 µgN/L	TP µgP/L	SRP µgP/L
Howard	9	21	2009	1.7	4.3	3.7
Ketchum	8	31	2009	0	218	119
Ki	9	21	2009	0	0.4	0.7
Loma	9	21	2009	0	19.4	3.5
Lone	8	27	2008	7	363.6	223
Lone	8	24	2009	0.9	335	32.6
Louise	8	23	2007	1.2	11.5	7.4
Louise	8	13	2008	0.5	6.8	3.3
Louise	8	10	2009	7.9	9.3	3.4
Martha	9	21	2009	0	5.5	1.5
McMurray	8	22	2007	19.2	19.2	6.4
McMurray	8	20	2008	16.6	12.2	3
McMurray	9	14	2009	0	6.5	5.5
Mirror	8	23	2007	1.6	42.4	7.7
Mirror	8	13	2008	30.1	23.8	7.1
Mirror	8	10	2009	2.4	16.9	3.5
Padden	8	23	2007	1	9.4	3.5
Padden	8	18	2008	0.5	0.8	1.9
Padden	8	10	2009	1.4	7.4	2.1
Pass	8	14	2007	0.7	29.9	4.6
Pass	8	27	2008	1.2	30.5	5.6
Pass	8	24	2009	0	31.7	6.6
Pine	8	14	2008	103.7	0.7	2.7
Reed	8	23	2007	3.6	17.4	4.9
Reed	8	13	2008	1.2	17.2	4.3
Reed	8	10	2009	19.8	39.8	7.8
Shoecraft	9	21	2009	3.5	4.5	1.7
Silver	8	19	2007	6.9	15.6	4.9
Silver	8	25	2008	12.8	18.4	3.8
Silver	9	8	2009	0.3	8.3	6.7
Sixteen	9	14	2009	0.4	15.8	4.1
Squalicum	8	15	2007	2.5	23.3	5.2
Squalicum	8	18	2008	7.1	25.5	3.7
Squalicum	8	18	2009	1.8	53.6	5.7
Squires	8	23	2007	1.8	10.1	3.6
Squires	8	13	2008	1.4	42.6	13.8

Lake	Month	Day	Year	NO_3 µgN/L	TP µgP/L	SRP µgP/L
Squires	8	10	2009	3	16.8	2.3
Summer	9	14	2009	0.5	16	3.8
Sunday	8	31	2009	0.6	17.6	4.6
Sunset	8	15	2007	1.9	25.4	3.2
Sunset	8	18	2008	1.3	22	2.2
Sunset	8	18	2009	0.9	21.3	2.7
Tennant	8	15	2007	2.5	107.7	4.9
Tennant	8	11	2008	10.4	49.4	3.4
Terrell	8	15	2007	1.2	45.8	3
Terrell	8	11	2008	1.8	19.2	6.8
Toad	8	22	2007	0.8	28.3	5.3
Toad	8	18	2008	55.9	9.2	3.5
Toad	8	18	2009	1	18.9	5.2
Vogler	9	8	2009	2.2	24.1	1.3
Wiser	8	15	2007	1.6	155	22.2
Wiser	8	11	2008	0.3	101.7	31.5

Lake	Month	Day	Year	Algal group	Chl group	TP group
Armstrong	8	31	2009	cyanobacteria	low	low
Beaver	9	14	2009	other	high	high
Big	8	22	2007	other	high	high
Big	8	20	2008	cyanobacteria	high	high
Big	9	14	2009	cyanobacteria	high	high
Bug	8	15	2007	other	low	high
Bug	8	18	2008	other	high	high
Bug	8	18	2009	cyanobacteria	low	high
Cain	8	23	2007	other	low	low
Cain	8	13	2008	other	low	low
Cain	8	10	2009	other	low	low
Campbell	8	14	2007	other	high	high
Campbell	8	27	2008	other	high	high
Campbell	8	24	2009	cyanobacteria	high	high
Cavanaugh	8	22	2007	other	low	low
Cavanaugh	8	20	2008	other	low	low
Cavanaugh	9	14	2009	other	low	low
Cedar	8	14	2008	other	low	low

Lake	Month	Day	Year	Algal group	Chl group	TP group
Clear	8	22	2007	cyanobacteria	low	high
Clear	8	20	2008	other	low	low
Clear	9	14	2009	cyanobacteria	low	low
Crabapple	9	21	2009	other	low	low
Cranberry	8	14	2007	cyanobacteria	high	high
Cranberry	8	27	2008	other	low	high
Cranberry	8	24	2009	cyanobacteria	high	high
Deer	8	27	2008	other	low	low
Deer	8	24	2009	other	low	low
Erie	8	14	2007	other	high	low
Erie	8	27	2008	other	low	high
Erie	8	24	2009	other	high	high
Fazon	8	15	2007	other	high	high
Fazon	8	11	2008	other	high	high
Goodwin	9	21	2009	other	low	low
Goss	8	27	2008	other	low	low
Goss	8	24	2009	other	low	low
Grandy	9	8	2009	other	low	high
Heart	8	14	2007	other	high	high
Heart	8	27	2008	other	high	high
Heart	8	24	2009	cyanobacteria	high	high
Honeymoon	8	24	2009	other	low	high
Howard	9	21	2009	other	low	low
Ketchum	8	31	2009	cyanobacteria	high	high
Ki	9	21	2009	cyanobacteria	low	low
Loma	9	21	2009	cyanobacteria	low	low
Lone	8	27	2008	other	high	high
Lone	8	24	2009	cyanobacteria	high	high
Louise	8	23	2007	other	high	low
Louise	8	13	2008	other	low	low
Louise	8	10	2009	other	low	low
Martha	9	21	2009	other	low	low
McMurray	8	22	2007	other	high	low
McMurray	8	20	2008	other	low	low
McMurray	9	14	2009	other	low	low
Mirror	8	23	2007	other	low	high

Lake	Month	Day	Year	Algal group	Chl group	TP group
Mirror	8	13	2008	other	low	high
Mirror	8	10	2009	other	low	low
Padden	8	23	2007	other	low	low
Padden	8	18	2008	other	low	low
Padden	8	10	2009	other	low	low
Pass	8	14	2007	cyanobacteria	high	high
Pass	8	27	2008	other	low	high
Pass	8	24	2009	other	high	high
Pine	8	14	2008	other	low	low
Reed	8	23	2007	other	low	low
Reed	8	13	2008	other	low	low
Reed	8	10	2009	other	low	high
Shoecraft	9	21	2009	other	low	low
Silver	8	19	2007	other	low	low
Silver	8	25	2008	other	low	low
Silver	9	8	2009	other	low	low
Sixteen	9	14	2009	other	low	low
Squalicum	8	15	2007	other	low	high
Squalicum	8	18	2008	other	low	high
Squalicum	8	18	2009	other	low	high
Squires	8	23	2007	other	high	low
Squires	8	13	2008	other	high	high
Squires	8	10	2009	other	low	low
Summer	9	14	2009	other	low	low
Sunday	8	31	2009	cyanobacteria	low	low
Sunset	8	15	2007	cyanobacteria	high	high
Sunset	8	18	2008	other	low	high
Sunset	8	18	2009	cyanobacteria	high	high
Tennant	8	15	2007	other	high	high
Tennant	8	11	2008	other	low	high
Terrell	8	15	2007	other	high	high
Terrell	8	11	2008	other	low	low
Toad	8	22	2007	other	high	high
Toad	8	18	2008	other	low	low
Toad	8	18	2009	other	low	low
Vogler	9	8	2009	other	low	high

Lake	Month	Day	Year	Algal group	Chl group	TP group
Wiser	8	15	2007	cyanobacteria	high	high
Wiser	8	11	2008	other	low	high